

**Understanding the Magnitude of Psychological Differences Between  
Women and Men Requires Seeing the Forest and the Trees**

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### **Abstract**

Whether women and men are psychologically very similar or quite different is a contentious issue in psychological science. This article clarifies this issue by demonstrating that larger and smaller sex/gender differences can reflect differing ways of organizing the same data. For single psychological constructs, larger differences emerge from averaging multiple indicators that differ by sex/gender to produce scales of a construct's overall typicality for women versus men. For example, averaging self-ratings on personality traits more typical of women or men yields much larger sex/gender differences on measures of the femininity or masculinity of personality. Sex/gender differences on such broad-gauge, thematic variables are large relative to differences on their component indicators. This increased effect magnitude for aggregated scales reflects gains in both their reliability and validity as indicators of sex/gender. In addition, in psychological domains such as vocational interests that are composed of many variables, at least some of which differ by sex/gender, the multivariate distance between women and men is typically larger than the differences on the component variables. These analyses encourage recognition of the interdependence of sex/gender similarity and difference in psychological data.

Keywords: sex differences, gender differences, effect magnitude, gender similarity hypothesis, femininity, masculinity

## **Understanding the Magnitude of Psychological Differences Between Women and Men Requires Seeing the Forest and the Trees**

The magnitude of differences between women and men is an unsettled issue in psychological science. One prominent claim, known as the *gender similarities hypothesis*, is that women and men are very similar on most psychological variables (Hyde, 2005, 2014). However, other experts maintain that, on the contrary, larger differences are common even in fundamental areas of human functioning such as personality (e.g., Archer, 2019; Lippa, 2005).

Such inconsistencies in scientific claims can be puzzling, given that they all rely on quantitative analyses of a large, shared database of psychological research. It is tempting to believe that either similarity or difference is the truth of the matter and to reject the alternative claim. Instead, those who care about this issue should pause and think more deeply. To further such understanding, this article takes crucial, but neglected, psychometric considerations into account. We show that claims of similarity and difference are both valid but can reflect differing ways of organizing the same data, and thus, metaphorically, they can be two sides of the same psychometric coin.

As a first step, given the lack of consensus among scientists about terminology pertaining to sex and gender, we define our key terms. Difficulties follow from the common view that the term *sex* pertains to biology and *gender* to socialization and culture—that is, sex is to gender as nature is to nurture. However, identifying differences as biologically influenced and/or socially constructed is a work in progress as scientists seek to understand how nature and nurture influence the psychology of women and men. Therefore, to avoid prejudging causality, we label differences by the hybrid neologisms of gender/sex (Schudson et al., 2019) and sex/gender (Fausto-Sterling, 2012) and apply these terms interchangeably. Finally, we define the words

*feminine* and *femininity* and *masculine* and *masculinity* as referring to human attributes, including traits and behaviors, that are more typical of women or men, respectively (Oxford, n.d.).

A large quantity of psychological research has addressed gender/sex differences and similarities. In evidence, the PsycINFO database includes 86,967 journal articles published from 1950 through 2020 that focus on these comparisons, as indicated by the assignment of the index term *human sex differences* to them (American Psychological Association, 2021). Among these articles are 713 reporting meta-analyses that reviewed portions of the research literature. In addition, many surveys have assessed psychological sex/gender differences, often with representative samples, as have many testing programs, conducted mainly in educational and counseling settings. Findings from these varied sources undergird the claims discussed in this article.<sup>1</sup>

The elusiveness of scientific consensus about the magnitude of sex/gender differences is not surprising, given the challenges of organizing this massive amount of empirical data. To address this issue, we argue that one important contributor to lack of consensus is insufficient consideration of relevant psychometric principles. We build our case by first reviewing experts' generalizations about the magnitude of gender/sex differences. Then we explain the psychometric principles by which the aggregation of data underlying effect sizes contributes to their magnitude. This analysis explains why psychological differences between women and men are often large on broad sex/gender-relevant psychological variables and simultaneously small on more narrowly defined indicators of such variables. Our analysis proceeds to consider the

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<sup>1</sup> For comparison, consider the benchmarks provided by following PsycINFO index terms for the same time period: *cognitive behavior therapy*: 16,241 articles, 533 meta-analyses; *leadership*: 21,972 articles, 165 meta-analyses; *cognitive development*: 28,108 articles, 137 meta-analyses; *organizational behavior*: 23,625 articles; 205 meta-analyses; *memory*: 98,422 articles, 587 meta-analyses; *personality*: 117,312 articles, 822 meta-analyses.

overall distance between men and women in psychological domains such as personality traits that are composed of many variables. Finally, the analysis concludes with reflections on the relevance of sex/gender differences and similarities to discourse on diversity in groups and organizations.

In this article, we assiduously avoid discussing particular causal explanations of gender/sex differences and similarities or indicating our personal preferences for any theories about causation. We encourage readers to apply their own interpretations to the patterns of similarity and difference that our analyses reveal. Some will emphasize the dependence of most psychological measures on self-report and the shaping of such responding and of masculinity and femininity more generally by social and cultural forces. Others will prefer to ascribe the findings we present to essential causes embedded in the evolution of women and men in the human species. Such dissimilar interpretations should inspire scientific research that compares and contrasts predictions from these and other theoretical positions. However, we have no such purpose in this article but instead strive to provide readers with a clearer view of the phenomena that require explanation.

### **Claims of Sex/Gender Similarities and Differences**

The small magnitude of most sex/gender differences is the central theme of Hyde's (2005) pioneering review of 46 meta-analyses, which yielded 128 effect sizes represented as standardized mean differences (i.e., the  $d$  statistic; Cohen, 1988) with 48% classified as small ( $d = |0.11| - |0.35|$ ) and 30% as very small ( $d = |0.10|$  or smaller). The largest effect size, aside from motor behaviors such as throw velocity was  $d = -0.91$  for tendermindedness, a facet of the personality trait of agreeableness.<sup>2</sup> Zell et al. (2015) seconded Hyde's similarity conclusion in an

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<sup>2</sup> To indicate the direction of sex/gender comparisons, a positive sign indicates larger male scores, and a negative sign indicates larger female scores. Pipe brackets indicate an absolute value.

expanded project that encompassed 106 meta-analyses reporting 386 effect sizes, which yielded 106 study-level effect sizes. Zell et al.'s mean effect size was  $d = |0.21|$ , ( $SD = 0.14$ ), with 46% classified as small and 39% as very small. The largest was  $d = |0.73|$ , for masculine and feminine personality traits.

Archer's (2019) subsequent review of sex/gender differences encompassed 131 meta-analyses and 89 estimates from other sources, summarized as 146 effect sizes. These other sources consisted of "(i) cross-national surveys of personality traits, social attributes, mate choice and sexuality; (ii) large-sample ( $N > 1000$ ) online studies; (iii) social surveys on attributes related to health and crime; and (iv) crime statistics" (Archer, 2019, p. 1393). The mean effect size was larger,  $d = |0.43|$ , ( $SD = 0.40$ ), with only 24% classified as small and 16% as very small. The largest consisted of 12 effect sizes greater than  $d = 1.00$ , considered very large, many of which pertained to crime and violence (e.g.,  $d = 2.54$ , for same-sex homicide).

Mirroring these contrasting presentations, the conclusions that writers of textbooks on the psychology of sex and gender have offered also have differed considerably. Some authors have emphasized gender/sex similarity (e.g., Bosson et al., 2019), whereas others have instead pointed to the presence of larger differences (e.g., Lippa, 2005).

To shed some light on these issues, we offer psychometric analyses that can promote understanding of the magnitudes of gender/sex differences and similarities. This analysis includes examples from relevant research but does not provide a general review of psychological differences and similarities, nor does it evaluate their causes.

### **Aggregation of Sex/Gender Differences on Single Dimensions**

Research on attitudes and personality traits provides an informative precedent for understanding the magnitude of sex/gender differences. In the 1960s, the relations between

psychological dispositions and relevant behaviors gained prominence when Wicker (1969), for attitudes, and Mischel (1968), for personality traits, showed that these relations were typically very weak. Challenges to these initially quite shocking conclusions soon emerged.

Demonstrating the importance of aggregation to the magnitude of effects, Fishbein and Ajzen (1974) showed that, despite most specific behaviors' weak relations to relevant attitudes, aggregations of such behaviors related strongly. Similarly, Epstein (1979, 1980) showed that, despite most specific behaviors' weak relations to relevant personality traits, aggregations of such behaviors related strongly. Thus, both attitudes and personality traits do relate strongly to general themes of relevant behaviors as, for example, when people high in religiosity engage in more religious behaviors than those who are low in this attitude.

Aggregations of behaviors that successfully predict attitudes or personality traits could be cumulated over occasions, contexts, or differing disposition-relevant behaviors. Based on such findings, a consensus emerged that behaviors relate more strongly to psychological dispositions to the extent that the behaviors match the generality or scope of a dispositional criterion (Ajzen & Fishbein, 1977; Epstein, 1983).

These demonstrations of the effects of aggregation did not reveal the psychometric principles underlying the improvement in prediction as a predictor encompasses a greater number and breadth of relevant components. Most discussions implicated the venerable psychometric principle that assessments of variables are more reliable when based on a greater number of valid indicators (Spearman, 1904). However, adequate understanding requires considering both the validity and the reliability of an aggregated predictor. For predicting sex/gender, for example, aggregating items from a domain, with every item having some validity for predicting sex/gender, increases the reliability of the predictor scale, which asymptotically

tends toward 1.00. The validity of a scale as a predictor of sex/gender also increases with the aggregation of items but is limited by the items' average interitem correlation. Specifically, the validity of a scale asymptotically tends towards the average item validity divided by the square root of the average of the interitem correlations. For a fixed average item validity, scale validity is a positive function of the number of items and is higher the lower the correlations between the items within the scale (see Appendix for derivation).

What are the implications of these insights for the magnitude of sex/gender differences? In general, aggregates of relevant items should more strongly predict sex/gender than single items in all domains of psychological functioning that differ between men versus women. If the items of an aggregated predictor are from the same domain and thus tend to be highly intercorrelated, the validity of the composite predictor increases with the number of items but not as strongly as it would if the items came from different domains and thus were more weakly intercorrelated. This insight thus reveals the principle underlying earlier researchers' claims that dispositions are more strongly predicted by aggregations of items that are not merely more numerous but also more diverse in content (Ajzen & Fishbein, 1977; Epstein, 1983). The diversity of a predictor increases as items encompass differing relevant domains and thus tend to be less highly intercorrelated. The implication of these principles for gender/sex research, in plain language, is that women and men differ more on psychological variables that are broadly construed, or thematic, than on more narrowly constituted variables.

A classic example of a large and broad multi-item composite variable relating strongly to gender/sex derives from research by Terman and Miles (1936) that aggregated a very wide range of questionnaire items that differentiated women and men. Their efforts yielded a 456-item Masculinity-Femininity Scale that yielded a gender/sex effect size of  $d = 2.53$  in a sample of 696



female and 604 male participants (Terman & Miles, 1936, p. 72). The large magnitude of this gender/sex difference is consistent with the principle that including many relevant items and drawing them from differing domains greatly increase prediction of gender/sex.

Despite this excellent prediction, the Terman and Miles (1936) research met with criticisms that their Masculinity-Femininity Scale encompassed a hodgepodge of diverse content and a scoring system that arbitrarily forced a single bipolar masculinity-femininity dimension (e.g., Constantinople, 1973). Addressing these criticisms entailed replacing the single bipolar dimension with two relatively independent unipolar dimensions, one for masculinity and the other for femininity (Bem, 1974; Spence & Helmreich, 1978) and examining these dimensions within various domains of psychological functioning. Therefore, we provide examples of this revised approach and explore their implications for understanding the magnitude of sex/gender differences.

### **Sex/Gender Differences in Behavioral Masculinity and Femininity**

Our first demonstration pertains to the relations of everyday behaviors to gender/sex, a considerably narrower domain than encompassed by the Terman and Miles (1936) scale. This demonstration relies on Athenstaedt's (2003) development of a multi-item index of behavioral masculinity and femininity.

To identify items that yielded different responses in women and men, Athenstaedt (2003) and her team initially wrote 191 preliminary items describing common observable behaviors from six domains: leisure time, occupation, social, relationships, education, and household. Athenstaedt then obtained ratings of these items' typicality for women or men and their desirability for each gender/sex, which enabled item selection for typicality and greater desirability for the more typical gender/sex. These criteria identified two sets of behavioral

items, 29 masculine, or male-typical, and 23 feminine, or female-typical.

To assess gender/sex differences in these behaviors, other participants rated how typical each of the behaviors was of themselves (on 7-point scales ranging from *not at all typical* to *very typical*). These participants were Austrians, 266 men and 310 women, recruited mainly from a school for vocational training or from sports courses for students and staff members at the University of Graz, with additional participants recruited by snowball sampling conducted by instructors and students of the same university.

Based on preliminary analysis of Athenstaedt's (2003) self-rating data, we removed one of these items as an outlier, "put on makeup," because it produced an extreme difference of  $d = -2.05$ . The remaining unit-weighted items yielded independent masculinity and femininity scales,  $r(574) = .06$ . Figure 1 shows the gender/sex difference in the  $d$  metric for each item and the two scales. The mean effect size for the individual items was  $\bar{d} = |0.51|$ . As expected, this effect size was considerably smaller than the effect sizes for the two multi-item scales: F (feminine) Behavior,  $d = -1.12$ ; M (masculine) Behavior,  $d = 0.92$ . (These effect sizes, as well as all others presented in this article, were not adjusted for potential statistical artifacts.)

To clarify the principles underlying these sizable scale effect sizes, Table 1 presents the properties of three behavioral scales produced from the Athenstaedt (2003) data: F Behavior, M Behavior, and F+M Behavior (composed of the feminine and the reverse-coded masculine items). Following the recommendation of Revelle and Condon (2019), we report three measures of reliability:  $\omega_h$ ,  $\alpha$ , and  $\omega_t$ .<sup>3</sup> Although  $\alpha$  is best known, it is effectively the average split-half reliability and should not be interpreted as a measure of internal consistency. The two model-

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<sup>3</sup> The omega function in the psych package provides these estimates (R Core Team, 2021; Revelle, 2021).

based estimates,  $\omega_h$  and  $\omega_t$ , reflect the amount of test variance that is due to one general factor ( $\omega_h$ ) or to all the factors in the test ( $\omega_t$ ). As expected, the reliability values for all scales were high for  $\alpha$  and  $\omega_t$  but lower for  $\omega_h$ , which dropped to near-zero for the scale that contained both the feminine and masculine items.

As also shown in Table 1, the average within-scale item correlations,  $\bar{r}_i$ , were low but, as expected, lower for the broader F+M scale that combined the feminine and masculine items. The average item validities,  $\bar{r}_{iy}$  (i.e., their prediction of sex/gender), were small and similar across the three scales. The scale validities were moderate for the feminine and the masculine scales and larger for the combined scale, reflecting its broader selection of items. Confirmation of the relevance of both reliability and validity to the scale validities follows from the close match between the empirical scale validities,  $r_{cy}$ , and the scale validities modeled by their statistical definition,  $r_{cy\ mod}$ , which incorporates both validity and reliability (see Appendix).<sup>4</sup>

Expressed in units of Cohen's  $d$ , the mean item effect sizes were moderate across the three scales and much smaller than the scale effect sizes. Consistent with the function that relates  $r$  to  $d$ , the effect sizes expressed in  $d$  were each two or more times the value of the corresponding validities expressed in terms of  $r$ .<sup>5</sup>

These data demonstrate that, as general trends, women and men differed substantially in their overall tendencies to enact these behaviors even though the differences were much smaller

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<sup>4</sup> We also calculated an F+M Behavior Short scale from the first halves of the femininity items and the reverse-coded masculinity items. Its scale effect size ( $d = -1.25$ ) was larger than those of the separate F Behavior and M Behavior scales ( $ds = -1.12$  and  $0.92$ ), which had similar numbers of items. This comparison showed that the gain of prediction for the F+M Behavior scale did not follow only from the greater number of items producing a more reliable scale. Because the items are more highly correlated within than between the M Behavior and F Behavior scales, the broader selection of items in the combined F+M Behavior scale increased the magnitude of the effect size because the validity of the scale also increased.

<sup>5</sup> The  $r$  to  $d$  function is the following:  $d = \frac{2r}{\sqrt{1-r^2}}$

on most of the specific behaviors. Among these behaviors (see Figure 1), many reflect the conventional domestic division of labor (e.g., shovel snow, do the ironing). Other behaviors pertain to leisure activities (e.g., watch sports on television, go to the ballet), workplace activities (e.g., work overtime, decorate the office with flowers), or social interaction in general (e.g., hold the door open for your partner, listen attentively to others).

The broader meanings that people attach to these behavioral trends stem from the human tendency to spontaneously infer others' psychological attributes as corresponding to their observed behaviors (Uleman et al., 2008). Inspection of Athenstaedt's (2003) behavioral items suggests underlying dispositions—in particular, an orientation of women toward relating to and caring for others and of men toward everyday chivalry and dealing with things. Thus, these data suggest thematic differences in the kinds of behaviors that are more typical of women versus men. However, given that these behaviors are heterogeneous in their psychological content, it is important to determine whether item aggregation also increases prediction of sex/gender when applied to specific domains of psychological functioning.

### **Sex/Gender Differences in the Femininity and Masculinity of Personality, Cognition, and Interests and Activities**

This second demonstration of aggregation pertains to personality, cognition, and interests and activities. Construction of these scales entailed aggregating sex/gender differences on feminine and masculine items to form two scales in each of these three domains. Sex/gender differences should be larger for each of these scales than for the average of their individual items.

This example relies on an instrument for gender/sex assessment, the Gender-Related Attributes Survey (GERAS), presented by Gruber et al. (2020). Construction of this self-report

instrument followed from the assembly of a preliminary item pool derived from prior research on psychological gender/sex differences as well as a study of self-reported gender identity (Pletzer et al., 2015). Analyses of the factor structure, reliability, and validity of the preliminary items yielded a three-level model. The third level consisted of two general variables, masculinity and femininity, each of which encompassed three domain-specific second-order factors pertaining to personality, cognition, and activities and interests. Although each of these second-order factors encompassed narrower first-order factors, for simplicity and brevity we confine our presentation to the items and scales of the second- and third-order variables.

The analyses we present derive from Gruber et al.'s (2020) validation study, which recruited participants from courses and announcement boards at the University of Salzburg and through bulletin boards in local civic centers. The resulting sample consisted of 471 native German speakers (230 men,  $M_{\text{age}} = 26.11$ ,  $SD = 8.86$ ; 241 women,  $M_{\text{age}} = 25.40$ ,  $SD = 8.98$ ). Approximately 70% were students, and 30% were from the general population. Using 7-point scales ranging from 1 = not at all [. . .] to 7 = very [. . .], these participants rated themselves on the attributes included in these scales in relation to the general population of men and women within the culture with which they predominantly associated themselves.

Figure 2 shows the sex/gender difference effect sizes for the individual items of the scales as well as for the femininity and masculinity scales within the personality, cognition, and activities and interests factors. The content of each of these six scales is distinctive: (a) for personality, the femininity scale focuses on expressivity and neuroticism, and the masculinity scale on risk-taking, assertiveness, and rationality; (b) for cognition, the femininity scale focuses on verbal skills and memory, and the masculinity scale on spatial and mathematical skills;<sup>6</sup> and

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<sup>6</sup> Self-report items are unusual assessments of cognition, a domain in which most measures present ability-relevant tasks (see Miller & Halpern, 2014).

(c) for interests and activities, the femininity scale focuses on female-typical social and sports interests, and the masculinity scale on male-typical social and sports interests.

The mean gender/sex item effect size for the masculinity and femininity scales, respectively, were as follows: for personality,  $\bar{d}s = 0.28$  and  $-0.48$ ; for cognition,  $\bar{d}s = 0.39$  and  $-0.24$ ; and for interests and activities,  $\bar{d}s = 0.48$  and  $-0.82$ . As expected, these item effect sizes were smaller than the corresponding scale effect sizes for masculinity and femininity, respectively: for personality,  $ds = 0.57$  and  $-0.86$ ; for cognition,  $ds = 0.65$  and  $-0.40$ ; and for interests and activities,  $ds = 0.83$  and  $-1.61$ .

To further clarify the principles underlying these aggregated effects, Table 2 presents the properties of three types of scales within the masculine and feminine domains and overall: F (feminine items), M (masculine items), and F+M (feminine and reversed-coded masculine items). The table reports the three measures of reliability:  $\omega_h$ ,  $\alpha$ , and  $\omega_t$ . Once again, the reliability values for all scales were higher for  $\alpha$  and  $\omega_t$  than for  $\omega_h$ , which, as expected, dropped to near-zero for the scales that combined the feminine and masculine items. The average within-scale item correlations,  $\bar{r}_i$ , were low but lower for the scales that combined feminine and masculine items, and lowest for the M+F All scale, which additionally combined items from all three domains. The average item validities,  $\bar{r}_{iy}$ , (i.e., their prediction of sex/gender) tended to be small, although larger for feminine interests and activities. The scale validities were moderate for the three feminine and three masculine scales, but in general larger for the combined M+F scales, reflecting their broader selection of items.

Confirmation of our assumptions about reliability and validity follows from the close match between the empirical scale validities,  $r_{cy}$ , and the scale validities modeled by their

statistical definition,  $r_{cy\ mod}$  (see Appendix). Expressed in units of Cohen's  $d$ , the mean item effect sizes were moderate, with the exception of the larger value for the feminine scale of interests and activities, and the scale effect sizes were much larger than the corresponding mean item effect sizes.

In summary, the aggregation of sex/gender-relevant items into broad masculinity and femininity scales produced larger gender/sex differences than the average effect sizes for the individual items. This generalization held whether the underlying items referred to behaviors, as in our first example, or to personality, cognition, or interests and activities, as in our second example. The reason for these gains is that the aggregated scores were a stronger predictor of sex/gender as the number of items in the predictor increased, with an enhanced gain to the extent that the items were not highly intercorrelated, as occurred in the scales that contained both masculine and feminine items.<sup>7</sup> The meaning of these findings is that men and women differ more strongly in these broadly defined features of personality, cognition, and interests and activities than they do in the narrowly defined tendencies that underlie these broad features.

### **Other Examples of Aggregation Increasing the Magnitude of Sex/Gender Differences**

Other examples of the effects of aggregation that are scattered throughout the research literature pertain to psychological variables that show a substantial sex/gender difference but were not designed to do so, as were femininity-masculinity scales. Their component indicators were selected to represent the variable and not for gender/sex typicality. Nevertheless, aggregation of the indicators of such a variable can increase the gender/sex difference.

One such example of aggregation occurred in a study of antisocial behavior among

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<sup>7</sup> Another example of the aggregation on single dimensions appears in the Supplemental Materials: Analyses of the Masculinity and Femininity Scales of the Bem Sex Role Inventory.

children in New Zealand that found boys engaging in more antisocial behavior than girls did. This gender/sex difference was much smaller on the measures of specific antisocial behaviors ( $\bar{d} = |0.25|$ ) than on an index averaged over seven component measures ( $d = 0.49$ ; Moffitt et al., 2001, p. 93). Similarly, a meta-analysis of child temperament found that boys and girls differed mainly in two areas: surgency and effortful control (Else-Quest et al., 2006). Specific indicators of temperament, which typically showed greater surgency in boys and effortful control in girls, yielded mainly small gender/sex differences ( $d$ s =  $|0.01|$  to  $|0.41|$ ). However, on the aggregated indexes of overall surgency or effortful control reported in some of the studies, differences were larger:  $\bar{d} = 0.55$  for boys' greater surgency and  $\bar{d} = -1.01$  for girls' greater effortful control.

In general, even for psychological constructs that merely happen to differ by gender/sex but were not designed to do so, aggregation of their specific indicators increases the magnitude of differences insofar as the underlying indicators also differ consistently between the gender/sexes. Aggregation thus produces a more reliable and valid index of the gender/sex differentiated attribute that these indicators have in common, which can be a psychological attribute such as effortful control that is greater in one sex/gender.

Another type of aggregation identifies an optimal set of items for predicting respondent sex/gender (Lippa, 2005). This procedure classifies participants by sex/gender, based on their responses to items in a particular domain such as occupational preferences or preferred hobbies. Specifically, the method assigns a *gender diagnosticity* score to each participant, defined as the probability that he or she is male (vs. female) as predicted by the weighted average of the items that most successfully classified respondents by gender/sex in a linear discriminant analysis. Gender/sex differences in these gender diagnosticity scores can be very large, for example,  $d = 2.58$  for occupational preferences (Lippa & Connelly, 1990).



What do these varied examples of measure aggregation mean for understanding the psychology of sex and gender? They give evidence of the simultaneous presence of gender/sex similarities and differences in psychological data. Our analyses indicate that women and men (or girls and boys) can differ considerably when their attributes are abstracted to display overall themes, that is, general trends whose components differ across persons. Women and men differ much more in such general female- or male-typical tendencies than in the specific indicators of these tendencies, each of which is influenced by other causes. Similarity and difference are thus compatible and intertwined. These principles apply to aggregation of any appropriate measures, not merely to the self-report measures that predominate in our examples.

As a further reflection on aggregation, consider whether men or women are somewhat more likely to engage in particular behaviors on single occasions. Do such instances actually matter in daily life? The answer is resoundingly yes if these behaviors aggregate over occasions and with similar behaviors to produce a notable patterning of behavior. For example, whether a woman or man engages in a single act of dominance such as interrupting someone makes little difference by itself, but consequential sex/gender differences emerge if men or women more often enact the behavior and related dominant behaviors. For example, research on deliberative groups has shown that, especially when men are in the majority and a majority rule for decisions prevails, they not only engage in hostile (i.e., nonsupportive) interruptions of women but also speak more often than women and with a greater feeling of self-efficacy (e.g., Karpowitz & Mendelberg, 2014). This gender/sex inequality in interruptions prevails even in the deliberations of the justices of the U.S. Supreme Court (Patton & Smith, 2017). Given replication of this pattern over time and situations, women and men would reap the consequences that follow from this male-dominant pattern of social interaction (Funder & Ozer, 2019). As this example

illustrates, understanding of sex/gender differences and similarities requires taking into account the patterning of behavior as it emerges over time, situations, and variants of the behavior.

### **Aggregation of Sex/Gender Differences in Multivariate Domains**

A different question about psychological sex/gender differences arises in domains such as personality that are composed of distinct variables, which usually are components of a single conceptual model. This question is whether women and men differ in general in such a domain. The answer follows from computing an effect size representing the distance between women and men in the multivariate space formed by the component variables.

A first thought might be instead to average the effect sizes of the component variables. To understand why this solution is inadequate, consider the simple example of assessing the distance between two cities, Chicago and Miami, in a two-dimensional space defined by north-south and east-west axes. This distance is not computed as the average of the intercity distances on the two dimensions but by the distance on a straight line connecting the two cities (i.e., the Euclidean distance). Multivariate effect sizes apply this logic to domains composed of two or more variables that are not necessarily independent.

Multivariate effect sizes, like univariate ones, yield a standardized difference between women and men. Specifically, the univariate  $d$  represents the difference between the female and male means on a dimension. The multivariate  $D$  represents the difference between the female and male centroids in the multivariate space. The centroid, the multivariate analogue of the univariate mean, is the point in multivariate space where the means from the component variables intersect. Computationally,  $D$  is the square root of the sum of the squared standardized sex/gender differences on the component variables, which are appropriately weighted so that incorporating new variables increases  $D$  only insofar as they contribute unique additional

information.<sup>8</sup> In other words, a new variable cannot enlarge  $D$  if it is statistically redundant with the variables already included in the sum (see Mahalanobis, 1936).

In summary, the logic of aggregation is different for multivariate and univariate arrays. Univariate aggregation averages responses on multiple indicators (e.g., items) of a single variable to produce a general measure of that variable (e.g., Masculine Personality). The sex/gender effect size,  $d$ , is the standardized difference between the female and male means on the variable. In contrast, the  $D$  effect size is also a standardized difference but between the female and male centroids of a multivariate space. This statistic indicates how similar or different women and men are in general on the variables that comprise a particular domain. Its interpretation benefits from also considering the univariate  $d$ s for the component variables. In other words,  $D$  adds information beyond the univariate  $d$ s by providing a statistically appropriate summary of them but does not substitute for them.

### **Multivariate Distances in Two-Dimensional Space**

Our first examples revisit the Athenstaedt (2003) and the Gruber et al. (2020) data by introducing Mahalanobis  $D$  to represent sex/gender differences in the two-dimensional space defined by the relevant masculinity and femininity scales. For the Athenstaedt data, Figure 3 thus shows the two-dimensional array defined by scales assessing the masculinity or femininity of behavior. The distributions of the data appear in a scatter plot and density plots for women and men on each of the two scales. The effect sizes for the individual univariate scales appear with

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<sup>8</sup> The Mahalanobis  $D$  differs from the Euclidean distance between the centroids by taking into account the correlations between the variables.  $D$  combines bivariate distances (i.e., the gender/sex difference on each dimension) in a manner similar to multivariate  $R$  combining bivariate correlations. Specifically, the individual distances are weighted by their independent effects by multiplying by the inverse of the pooled correlation matrix of the various predictors. See Del Giudice (2021a) for exposition on how the Mahalanobis distance compares to a simple Euclidean distance between two centroids. Depending on the pattern of correlations, the Mahalanobis distance can be greater or less than the Euclidean distance.

the density plots:  $d = 0.92$  for M Behavior and  $d = -1.12$  for F Behavior. The bivariate scatter plot displays the centroids of the two-dimensional array, with Mahalanobis  $D = 1.97$  representing the distance between these centroids.

For the Gruber et al. (2020) data, Figure 4 shows the two-dimensional arrays defined by the masculinity and femininity scales for each of Gruber et al.'s three domains: personality, cognition, and interests and activities as well as for the composite data that combined the three domains. Notable are the univariate and multivariate gender/sex differences for interests and activities, which are larger than those for personality or cognition and even slightly larger than for the combined data. For all four of these displays, the Mahalanobis  $D$  is greater than the  $d$  effect sizes for the component masculinity or femininity scales.

Now we turn from these bivariate examples to multivariate analyses in two psychological domains for which psychometricians have developed outstanding technologies of assessment: personality and vocational interests.

### **Multivariate Differences in Multidimensional Space**

***Personality traits.*** Personality is an appropriate domain for examining multivariate effect sizes because decades of research have established its multidimensionality. The five-factor, or Big Five, model provides the most popular representation of the dimensions of personality (Digman, 1990; Goldberg, 1992). To varying extents, men and women differ on each of these dimensions. For example, in a large internet-based survey of 5,417 female and 2,901 male students, Nofle and Shaver (2006, Study 1) found the following gender/sex differences: Conscientiousness,  $d = -0.28$ ; Agreeableness,  $d = -0.22$ ; Neuroticism,  $d = -0.49$ ; Openness to Experience,  $d = 0.08$ ; and Extraversion,  $d = -0.16$ , producing a mean effect size of  $\bar{d} = |0.25|$ . A multivariate calculation yielded Mahalanobis  $D = 0.84$  (Del Giudice, 2009).

Notably, sex/gender differences tend to be small for the individual Big Five variables, except for Neuroticism. These results are not surprising, given that the subdimensions, or facets, of Big Five dimensions sometimes show opposite directions for sex/gender-differences (Kajonius & Johnson, 2018). For example, Extraversion encompasses the facets of Warmth, which is greater in women, and Dominance, which is greater in men. Therefore, the overall sex/gender difference in Extraversion is small. This mixing of female- and male-typical traits within dimensions also prevails in the Big Two, which forms a Stability dimension from Emotional Stability (i.e., Neuroticism), Conscientiousness, and Agreeableness, and a Plasticity dimension from Extraversion and Openness to Experience (Digman, 1997).

Some other systems for representing personality, which less often place male-typical and female-typical items on the same scale, predict sex/gender more strongly, as does the Sixteen Personality Factor Questionnaire (16PF, Conn & Rieke, 1994). Del Giudice et al. (2012) thus analyzed data from the 1993 U.S. standardization sample of the 16PF, 5th Edition (5,417 female and 2,901 male respondents). With personality assessed by this measure, the mean sex/gender effect size was  $\bar{d} = |0.26|$ . The largest univariate effects in the female direction were  $d = -1.34$  for Sensitivity and  $d = -0.50$  for Warmth and in the male direction were  $d = 0.32$  for Emotional Stability and  $d = 0.27$  for Dominance. With the dimensions represented in multivariate space, Del Giudice et al. calculated Mahalanobis distance as  $D = 1.49$ , thus much larger than  $D$  for the Big Five and larger than any of the univariate effect sizes for the 16PF.

Feminine and masculine themes have also emerged prominently in a representation of personality traits by a circular structural model, known as the *circumplex* (Gurtman, 2009). In this model, personality traits form a circular array defined by two principal, higher-order dimensions, which in Wiggins' (1996) interpersonal circumplex are Agency (or

dominance/instrumentality) and Communion (or warmth/expressiveness). Component variables are located on a circular continuum of similarity and difference so that each variable represents a blend of these two orthogonal dimensions that define the space (see Figure 5).

Because the interpersonal circumplex has a two-dimensional agency-communion structure by design, it should produce gender/sex differences that correspond to those for the masculinity (or agency) and femininity (or communion) scales in classic personality measures of gender identity (e.g., Bem, 1974). Of interest therefore is Lippa's (2001, p. 293) meta-analysis of five studies that assessed gender/sex differences in the circumplex (two for the interpersonal circumplex, and three for the closely related circumplex of interpersonal problems). As shown in Figure 5, the meta-analytic effect sizes for the gender/sex differences on the individual circumplex variables ranged from  $d = |0.14|$  to  $|0.61|$  and averaged to  $\bar{d} = |0.44|$ . Our computation of Mahalanobis  $D$  for one of the datasets from Lippa (2001) yielded  $D = 0.67$ . The small increment of  $D$  beyond the component univariate effect sizes reflects the high correlation between the dimensions with larger effect sizes.

Lippa's (2001) meta-analysis obtained the expected tendencies of men toward agency and women toward communion (see Figure 5). However, these trends were somewhat smaller on the Masculine Instrumentality versus Feminine Expressiveness axis than on the related but more evaluatively negative axis of Arrogant/Calculating ( $\bar{d} = 0.60$ ) versus Unassuming/Ingenuous ( $\bar{d} = -0.61$ ). A similar pattern emerged in Gurtman and Lee's (2009) study that implemented a different method of assessing gender/sex differences (*octant scores* within the circumplex).

In conclusion, models of personality have produced differing estimates of the overall similarity versus difference of women and men. These discrepancies tend to reflect how well each measurement model isolates the communal or agentic tendencies that most differentiate

female and male personality. In all models, the meaning of the  $D$  multivariate distance statistic emerges from considering it in conjunction with its component univariate effect sizes.

**Vocational interests.** Vocational interests provide another illustration of gender/sex differences in a multivariate domain. To take account of multidimensionality, Holland (1959, 1997) proposed a typology of six variables, designed to bridge between personality traits and work environments: (a) Realistic: interest in working with things or outdoors; (b) Investigative: interest in science, inclusive of mathematics and physical, social, biological, and medical sciences; (c) Artistic: interest in creative expression, inclusive of writing and the visual and performing arts; (d) Social: interest in working with and helping others; (e) Enterprising: interest in leadership or persuasive roles directed toward economic objectives; and (f) Conventional: interest in working in structured environments, especially in business settings. A hexagon representing these variables places the more highly related ones in closer proximity (see Figure 6).

To integrate research comparing the vocational interests of men and women, Su et al. (2009) meta-analyzed norming data for U.S. and Canadian samples reported in technical manuals for 47 interest inventories published between 1964 and 2007 ( $N = 503,188$  respondents, sample mean ages of 12.50 to 42.55 years). The results were that men scored higher than women did on Realistic ( $\bar{d} = 0.84$ ) and Investigative ( $\bar{d} = 0.26$ ) interests and that women scored higher than men did on Artistic ( $\bar{d} = -0.35$ ), Social ( $\bar{d} = -0.68$ ), and Conventional ( $\bar{d} = -0.33$ ) interests. Enterprising showed little difference ( $\bar{d} = 0.04$ ). The grand mean of these effect sizes was  $\bar{d} = |0.45|$ .

The most popular measure of vocational interests is the Strong Interest Inventory. Morris (2016) reported sex/gender differences on this measure for a large cross-sectional sample of U.S.

residents who completed this test between 2005 and 2014 ( $N = 1,283,110$  respondents; ages 14 to 63). These analyses found that men scored higher on Realistic ( $d = 1.14$ ), Investigative ( $d = 0.32$ ), Conventional ( $d = 0.23$ ), and Enterprising ( $d = 0.22$ ) interests, and women scored higher on Artistic ( $d = -0.19$ ) and Social ( $d = -0.38$ ) interests. Most of these effect sizes were thus consistent with the Su et al. (2009) meta-analysis: Men were higher on Realistic and Investigative interests, and women on Artistic and Social interests. The mean of Morris's effect sizes was  $d = |0.41|$ .

Comparing women and men in this multivariate space yielded  $D = 1.50$  for Morris's (2016) study of the Strong Interest Inventory and  $D = 1.40$  for Su et al.'s (2009) meta-analysis (R. Su, personal communication, November 25, 2019). As expected, these multivariate effect sizes were thus much larger than the average of the differences for the six individual scales.

Providing a different type of multivariate summary of interest scores, Prediger (1982) derived two bipolar higher-order dimensions within Holland's hexagon: preferences for working with (a) things versus people and (b) data versus ideas (see Figure 6).<sup>9</sup> Assessments of women and men on these metadimensions have consistently produced a substantial difference only on the Things-People dimension, with men preferring things relative to women preferring people (see Su & Rounds, 2015). Su et al.'s (2009) meta-analysis thus found a large Things-People gender/sex difference ( $\bar{d} = 0.93$ ), as did Morris's (2016) analysis of the Strong Interest Inventory ( $d = 1.01$ ). These values were larger than all but one of the gender/sex differences on the individual dimensions (i.e., Realistic in the Morris analysis).

The even larger Mahalanobis  $D$  summarized the overall distance between the vocational

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<sup>9</sup> The computation of these dimensions maps the six interest types onto the two higher-order dimensions: (a) Things-People =  $(2.0 \times R) + (1.0 \times I) - (1.0 \times A) - (2.0 \times S) - (1.0 \times E) + (1.0 \times C)$  and (b) Data-Ideas =  $(0.0 \times R) - (1.7 \times I) - (1.7 \times A) + (0.0 \times S) + (1.7 \times E) + (1.7 \times C)$ .



interests of women and men. To identify which particular interests differed in women versus men, interpreters should refer to the Things-People dimension and the six specific dimensions. Once again, the multivariate effect size supplements but does not substitute for univariate (and, if available, bivariate) effect sizes.

### **Discussion**

We invite our readers to embrace the complexity of the psychology of sex and gender by taking into account gender/sex similarity and difference at the differing levels of analysis explored in this article. One lesson is that gender/sex differences become larger by averaging relevant individual indicators that differ by gender/sex to yield measures of broader masculine or feminine psychological tendencies. A second lesson is that differences are larger on assessments of the overall difference between women and men in multidimensional domains such as personality in which they differ on the component dimensions. Although these insights about magnitude do not speak to the causes of similarity and difference, they clarify the phenomena that require explanation.

The first method by which gender/sex differences increase in magnitude relies on the principle that individual indicators of a variable consist of true score (what the researcher intends to measure) and error score (irrelevant influences; Lord & Novick, 1968). Averaging responses across relevant indicators ordinarily provides a more precise estimate of true score variance while reducing error score variance, producing a more reliable aggregated measure of a target psychological variable. In addition, given that the validity of an aggregated criterion shows greater gains to the extent that its components are not highly correlated, sex/gender differences tend to be larger on broader sex/gender-relevant criteria that draw from differing psychological domains.

The second method by which effect sizes estimating gender/sex differences become larger assesses the distance between men and women in psychological domains that are composed of two or more variables. This method appropriately combines the differences on the component variables to yield a multivariate difference (Mahalanobis  $D$ ) between the female and male centroids of the multivariate space. Such analyses answer the question of how different or similar women and men are in general in a psychological domain such as personality.

These insights about effect magnitudes are important although our presentation has some limitations. One is that, for brevity and simplicity, we have reported effect magnitudes only in the popular metric of standardized average differences. However, readers can easily transform these univariate and multivariate effect sizes into any of several alternative metrics, such as the percentage of overlap of the female and male distributions (see Del Giudice, 2021b; Revelle, 2021).

Another limitation is that psychological research on sex/gender differences and similarities has almost always assessed a binary comparison even though a small percentage of people are biologically intersexed (Sax, 2002) or self-identify as nonbinary or transgendered (e.g., Meerwijk & Sevelius, 2017). Because the proportion of individuals not in the cisgendered binary is increasing, at least in the United States (Jones, 2021), future researchers may routinely take account of these other categories, but this practice is rare in current or earlier presentations. Similarly, the intersectionalities of sex/gender with age, race, sexualities, and other social categories only occasionally appear in psychological studies of sex/gender differences and similarities. Nevertheless, the psychometric principles presented in this article would also illuminate the magnitudes of category differences that result from more complex arrays of gender/sex social categories.

### Claims of Gender/Sex Similarity and Difference

A return to the opening theme of this article is in order: Scientists disagree about magnitude of sex/gender differences in research findings, with some maintaining that similarity is the correct overall description of these findings, and others maintaining that large differences are common. Our analyses have transcended this debate by explaining how smaller and larger differences can be linked: (a) small differences on specific variables can function as components of a larger difference on a broader, thematic variable such as the femininity of personality, and (b) small differences on variables within a multivariate psychological domain such as vocational interests can contribute to a larger multivariate difference for the domain as a whole.

Despite the importance of these insights, inconsistencies in aggregation are surely not the only cause of the discrepancies between the existing large-scale quantitative reviews of gender/sex differences, that is, between the generally larger differences in the Archer (2019) review than the Hyde (2005) and the Zell et al. (2015) reviews. No doubt, the major reason for inconsistency in magnitudes pertains to what these reviews included, given untold degrees of freedom in assembling their databases from hundreds of published meta-analyses. Consistent with this freedom, the authors' decision rules about inclusion and exclusion differed. Consider, for example, Hyde's (2005, p. 582) simple, but ambiguous, selection criterion of "the major meta-analyses that have been conducted on psychological gender differences" and Archer's (2019, p. 1385) exclusion of "studies on attributions or attitudes, except where these relate to core topics, such as sexuality and interests"). Moreover, Archer searched beyond meta-analyses to include information such as crime statistics. For example, included only by Archer were statistics pertaining to violent crime, homicide, partner homicide, rape, and violent computer game use, all contributing effect sizes greater than 1.00.

The aggregation issues analyzed in this article would have some influence on the effect magnitudes reported in these three general syntheses. Unfortunately, however, meta-analysts have seldom coded the aggregation of indicators underlying the measures reported in primary studies. In addition, the synthesized meta-analyses rarely included both aggregative and component measures, allowing later reviewers to choose which effect sizes to import. In an exceptional example, the Else-Quest et al. (2006) meta-analysis of child temperament did present both types of measures. In her review, Hyde (2014) did not include the effect sizes for the aggregative measures of effortful control ( $\bar{d} = -1.01$ ) and surgency ( $\bar{d} = 0.55$ ) but cited some of the smaller component effect sizes. Archer (2019) included the aggregative effect size for effortful control, plus several of the smaller component effect sizes. Zell et al (2015) reported only a grand mean effect size ( $\bar{d} = |0.16|$ ) averaged over the temperament effect sizes in Else-Quest et al.

In another example of contrasting selections from meta-analyses, Hyde (2005) included effect sizes for 6 of the 12 domains from Table 1 of the Hedges and Nowell (1995) meta-analysis of cognitive abilities, omitting the larger effect sizes (e.g., mechanical reasoning,  $d = 0.83, 0.72$ ) as well as those for writing ability reported in Table 2 (ranging from  $-0.55$  to  $-0.61$ ). Zell et al. (2015) omitted this meta-analysis entirely, but Archer (2019) incorporated eight of its findings, including the relatively large effect sizes for mechanical reasoning and writing.

As suggested by these examples, reviewers' decisions to include or exclude effect sizes differing in magnitude and sometimes in aggregation can be inconsistent. To help clarify these issues, it would be helpful if meta-analysts coded the degree of aggregation of studies' measures. We also recommend that researchers who synthesize meta-analyses report mean effect sizes for various categories of studies that can exist within individual meta-analyses as well as overall as

Hyde (2005, 2014) and Archer (2019) have done.

Relevant to the effect sizes reported in this article, we declined to correct them for reliability, and thus our data understate the size of the true effects (Booth & Irwing, 2011; Del Giudice et al., 2012; Schmidt & Hunter, 1999). We made this choice for two reasons. The first reason is to express the aggregated effect sizes in the same units (observed rather than latent) as the item effect sizes. The second reason pertains to the standard problem of which adjustment to use (Revelle & Condon, 2019). The tradition of adjusting effects by the square root of the reliability estimated by coefficient alpha necessarily overinflates the effect size because alpha underestimates reliability. Adjusting by a model-based estimate of reliability, such as  $\omega_t$ , is perhaps better, but still an underestimate. Adjusting for  $\omega_t$  would increase the effect size estimates that we have reported by roughly 5-7%. Readers should thus realize that the aggregated effect sizes presented in this article would be somewhat larger with the application of such corrections.

We again emphasize that our limited goals precluded providing a general review of psychological gender/sex differences. Instead, our purpose is to demonstrate that understanding the magnitude of gender/sex differences benefits from taking into account both the aggregation of relevant indicators of single variables and the estimation of overall effects in multivariate domains. The principles revealed by this analysis thus inform the science of sex and gender beyond the particular variables used for illustrations.

The psychometric principles invoked in this article would hold for the data of any time or place or culture, despite variation in the content of gender/sex differences. As an extreme example, Mead (1935) described a culture in which agency and communion were reversed from Western cultures, yielding agentic women and communal men. Others have challenged Mead's

claim (see Shankman, 2009), but if there is or was such a culture, aggregation would still work just fine. The agency-communion content of the personality traits typical of men and women would merely be opposite from that of Western (and many other) cultures.

In summary, our conclusion is that sex/gender comparisons in psychological research produce both large and small differences, with the smaller differences often being components of the larger differences. These findings raise questions about the correspondence between people's beliefs about women and men in relation to gender/sex differences at the differing levels of analysis in scientific findings that our analyses have displayed. Social cognitive research has shown that in general people do aggregate their observations to more abstract beliefs, with varying degrees of accuracy (Kunda & Nisbett, 1986). Manifesting intuitive aggregation, people volunteer primarily personality-type attributes when asked to describe women or men in their own words although physical characteristics, social roles, and cognitive abilities also emerge (e.g., Broverman et al., 1972; Ghavami & Peplau, 2013). Moreover, suggesting higher-level abstraction, the majority of the personality traits volunteered in these studies cohere thematically into the two families of agency and communion (e.g., Broverman et al., 1972; Williams & Best, 1990), with agentic traits ascribed more to men and communal more to women (Eagly et al., 2020). Such trends invite closer consideration of the relations between gender stereotypes and scientific findings, an important topic that is beyond the scope of this article.

Another concern is that recognizing the influence of aggregation on effect magnitude might discourage researchers from trusting effect sizes at all. Such a reaction could follow from the overly simple interpretations prevailing in psychology of what magnitudes should be considered small, medium, and large and therefore less or more important. These interpretations ignore how measures are constituted. The solution does not lie in returning to reliance on

statistical significance to evaluate effect magnitude. Rather, progress in understanding effect magnitude requires taking into account the properties of measures along with effect sizes, and we hope that this article will encourage progress in this direction.

### **Reflections on Difference and Similarity**

We now briefly depart from our focus on the psychometrics of sex/gender comparisons because we suspect that our insights that sex/gender differences can be simultaneously large and small might appear to some readers to threaten gender equality. However, just as we have urged more complex thinking about the magnitude of sex/gender differences, we urge more complex thinking about gender equality.

Consider that acknowledging gender/sex differences can sometime help to redress inequalities. For example, evidence that women's life goals tend to be more communal than those of men has inspired efforts to attract women into STEM by incorporating collaborative, prosocial principles into the practice of science (Diekman et al., 2017). In addition, recognizing women's greater communion may improve their access to employment in view of labor market analyses showing that more jobs increasingly require higher level of social skills (Deming, 2017; U.S. data). Furthermore, research on the so-called *female advantage* in leadership has shown that women's tendencies toward more collaborative and participative leadership can confer benefits for groups and organizations in many contexts (Eagly, 2007; Post, 2015). Such considerations display the limitations of assuming that sex/gender difference necessarily disables women or that gender equality requires the psychological similarity of women and men.

Psychological differences between identity groups can be consistent with social equality to the extent that groups and organizations respect and value diversity, not only in demographic characteristics but also in the attitudes, values, personality, preferences, and competencies that

are sometimes correlated with these characteristics. In fact, advocates for diversity have championed the idea that diverse groups are more effective in solving problems and predicting events than are homogeneous groups. Their reasoning follows from the assumption that *cognitive heterogeneity*—differences between identity groups in knowledge, perspectives, preferences, and heuristics—yields more tools and resources for doing the work of groups and organizations (e.g., Page, 2008). Even if such diversity gains can be overstated (Eagly, 2016), they would not follow from gender/sex diversity if women were the psychological clones of men.

Regardless of any advantages or disadvantages that follow from gender/sex differences and similarities, responsible scientists act as honest brokers by producing and communicating valid findings to increase scientific knowledge and contribute to evidence-based policy (Eagly, 2016). To this end, we recommend recognizing the forest and the trees of sex/gender differences and similarities. It is necessary to step away from the individual trees, perhaps to a hilltop, to observe the patterning of trees in a forest. Similarly, the patterning of psychological gender/sex differences can be difficult to discern in narrowly defined attributes but emerges more strongly in general trends. It follows that neither similarity nor difference prevails but instead a more complex intertwining of these two types of findings.



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**Table 1. Attributes of Athenstaedt (2003) Scales of Behavioral Femininity and Masculinity**

Scale	$k$	$\omega_h$	$\alpha$	$\omega_t$	$\bar{r}_i$	$\bar{r}_{iy}$	$r_{cy}$	$r_{cy\ mod}$	$\bar{d}_i$	$d$
F Behavior	29	0.49	0.87	0.88	0.19	-0.26	-0.49	-0.56	-0.55	-1.12
M Behavior	23	0.64	0.84	0.85	0.19	0.22	0.42	0.46	0.46	0.92
F+M Behavior	52	0.02	0.83	0.85	0.09	-0.24	-0.70	-0.73	-0.51	-1.94

**Note.** Scales were formed from items loading on F (femininity) and M (masculinity) factors. F+M included all items, with the masculinity items reverse-coded.

$k$  = number of items. The next columns show three estimates of reliability:  $\omega_h$  = test variance due to one general factor;  $\alpha$  = coefficient alpha;  $\omega_t$  = test variance due to all of the factors. The subsequent columns show  $\bar{r}_i$  = average within-scale item correlation;  $\bar{r}_{iy}$  = average item validity;  $r_{cy}$  = observed scale validity;  $r_{cy\ mod}$  = modeled scale validity;  $\bar{d}_i$  = average item Cohen  $d$ ;  $d$  = scale Cohen  $d$ .

**Table 2***Attributes of Gruber et al. (2020) Femininity and Masculinity Scales of Personality, Cognition, and Interests and Activities*

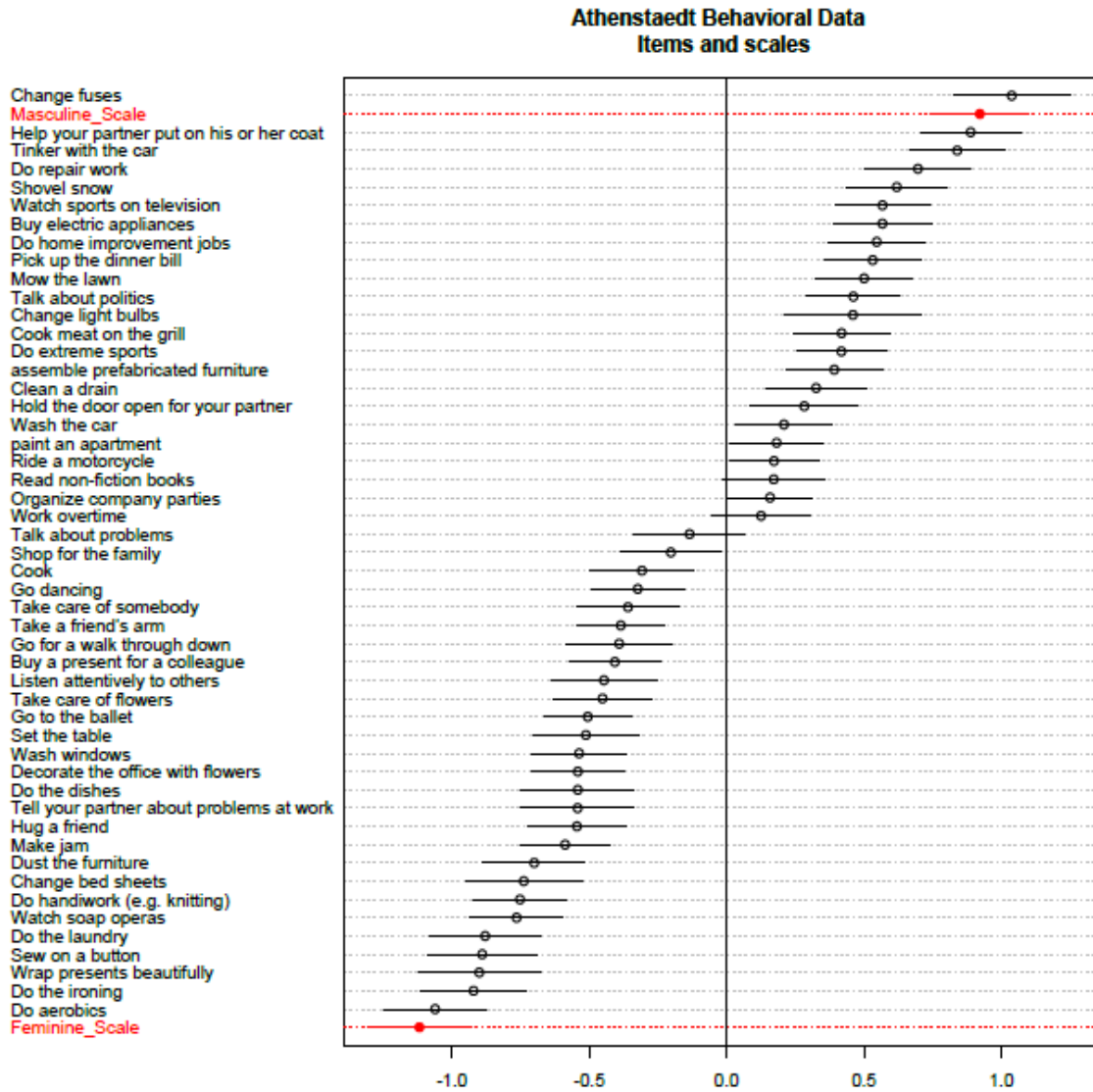
Scale	$k$	$\omega_h$	$\alpha$	$\omega_t$	$\bar{r}_i$	$\bar{r}_{iy}$	$r_{cy}$	$r_{cy\ mod}$	$\bar{d}_i$	$d$
M Personality	10	0.01	0.51	0.65	0.16	0.14	0.27	0.28	0.28	0.57
F Personality	10	0.25	0.80	0.84	0.28	-0.23	-0.39	-0.39	-0.48	-0.86
M Cognition	7	0.30	0.73	0.84	0.28	0.19	0.31	0.31	0.39	0.65
F Cognition	7	0.42	0.70	0.76	0.25	-0.12	-0.19	-0.20	-0.24	-0.40
M Interests & Activities	8	0.48	0.75	0.78	0.27	0.23	0.38	0.38	0.48	0.83
F Interests & Activities	8	0.48	0.75	0.79	0.27	-0.38	-0.62	-0.63	-0.82	-1.61
M+F Personality	20	0.09	0.77	0.81	0.14	0.18	0.38	0.42	0.43	0.93
M+F Cognition	14	0.05	0.67	0.74	0.13	0.15	0.35	0.36	0.31	0.77
M+F Interests & Activities	16	0.09	0.75	0.79	0.16	0.30	0.66	0.65	0.65	1.73
M All	25	0.25	0.81	0.83	0.15	0.18	0.43	0.43	0.37	0.97
F All	25	0.23	0.83	0.85	0.17	-0.25	-0.55	-0.55	-0.52	-1.41
M+F All	50	0.26	0.85	0.86	0.10	0.21	0.62	0.63	0.45	1.61

**Note.** Scales were formed from items loading on F (femininity) and M (masculinity) factors for Personality, Cognition, and Interests and Activities and for all domains. M+F scales included feminine and masculine items, with the masculinity items reverse-coded. M All, F All, and M+F All included the items from all three domains.

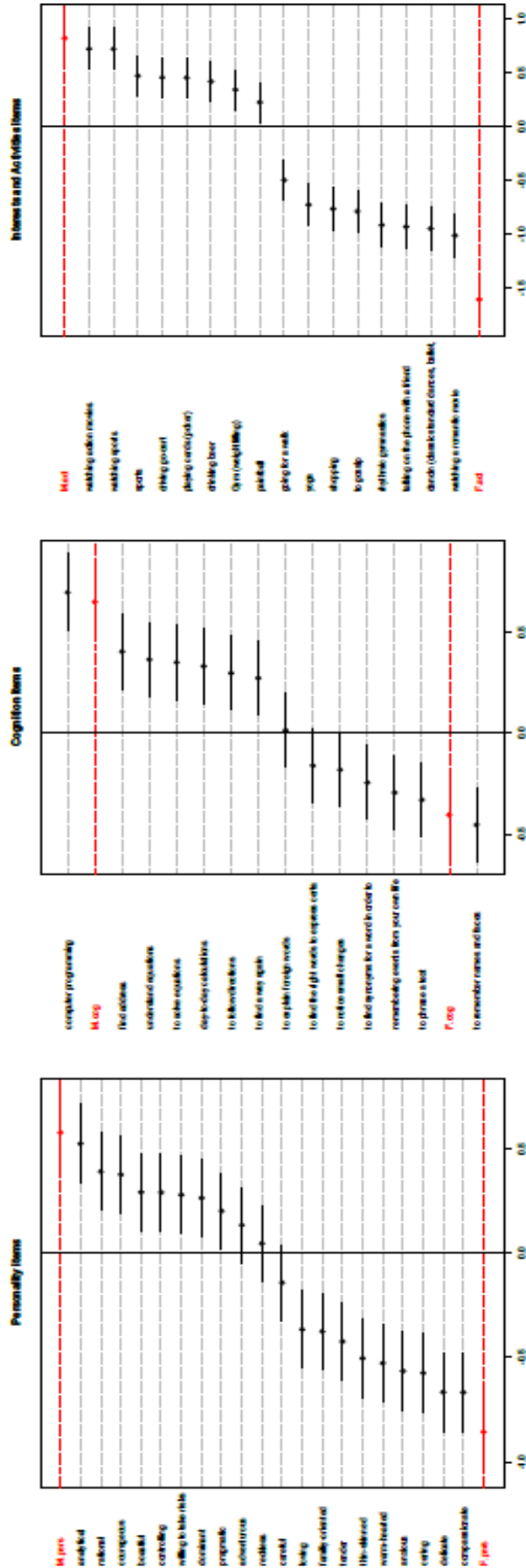
$k$  = number of items. The next columns show three estimates of reliability:  $\omega_h$  = test variance due to one general factor;  $\alpha$  = coefficient alpha;  $\omega_t$  = test variance due to all of the factors. The subsequent columns show  $\bar{r}_i$  = average within-scale item correlation;  $\bar{r}_{iy}$  = average item validity;  $r_{cy}$  = observed scale validity;  $r_{cy\ mod}$  = modeled scale validity;  $\bar{d}_i$  = average item Cohen  $d$ ;  $d$  = scale Cohen  $d$ .

**Figure 1**

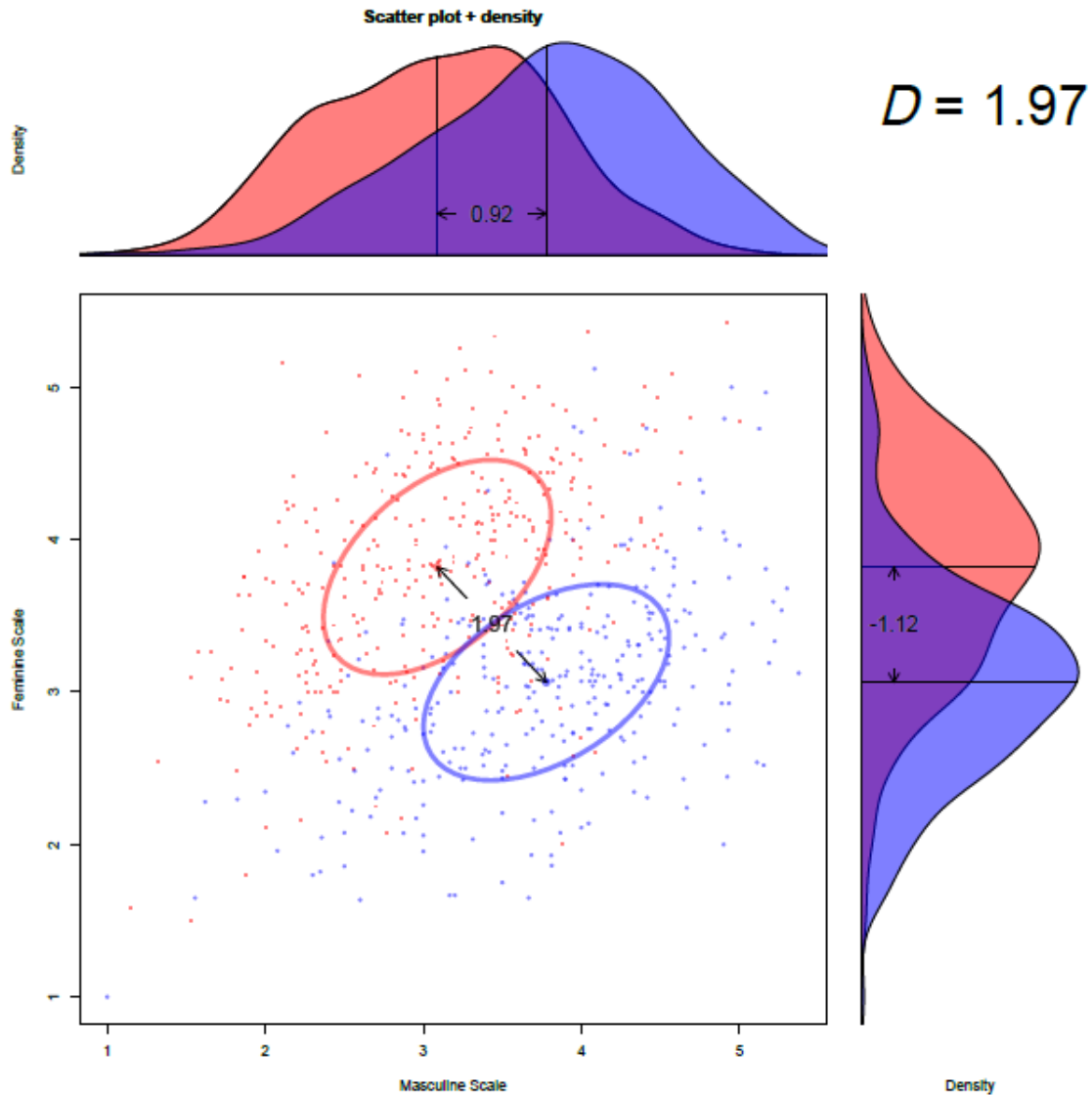
*Effect Sizes with 95% Confidence Intervals for Athenstaedt (2003) Behavioral Items and Behavioral Masculinity and Femininity Scale.*



**Figure 2**  
*Effect Sizes with 95% Confidence Intervals for the Gruber et al. (2020) Masculinity and Femininity Personality, Cognition and Interest Items and Scales*

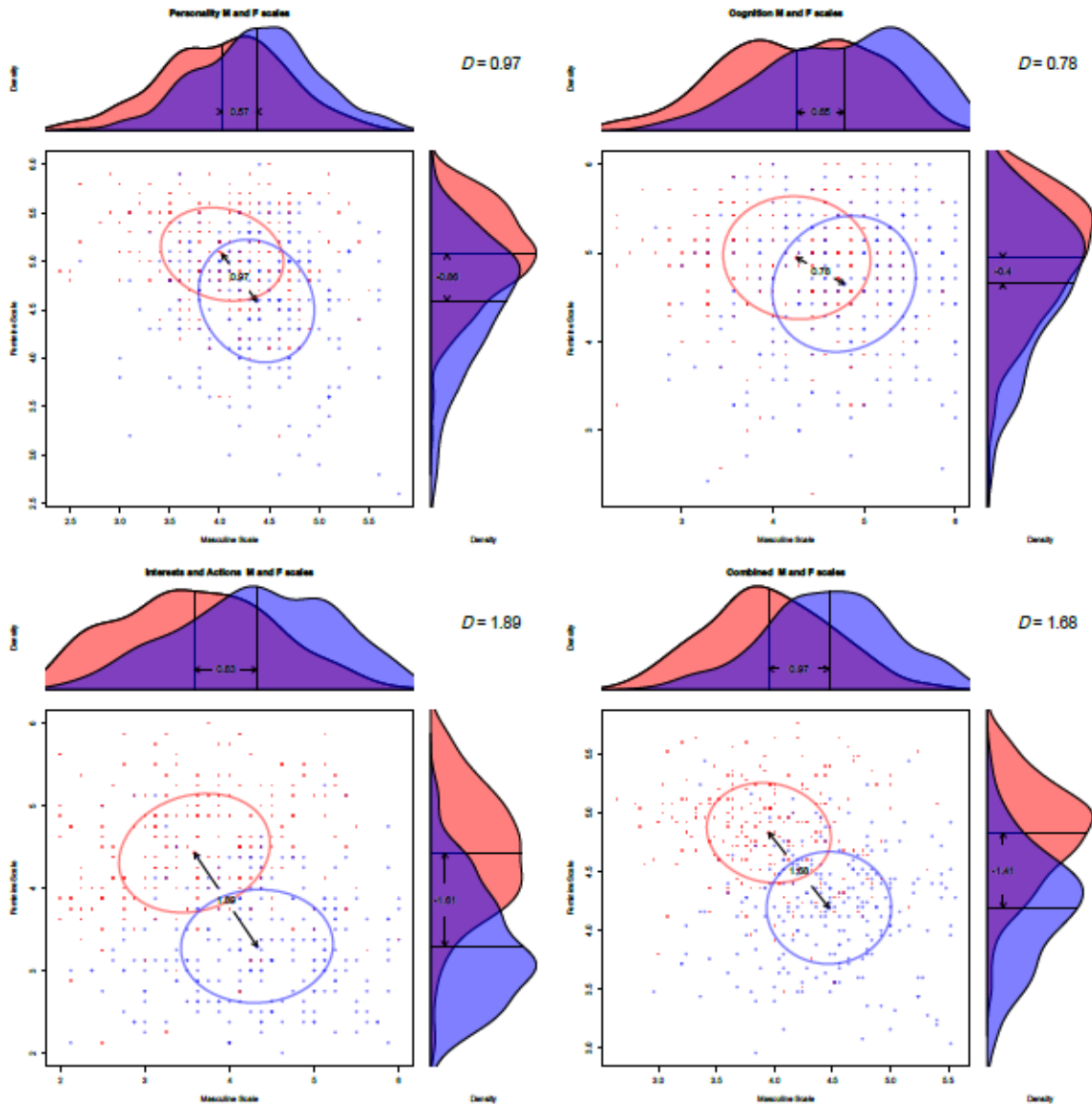


**Figure 3**  
*Plot of the Athenstaedt (2003) Masculine and Feminine Behavioral Scales*



*Note:* Scatter plot of the Masculine and Feminine scales from the Athenstaedt (2003) data set for males (blue) and females (red). The scatter plots show the individual participants, the ellipses reflect one standard deviation from the group centroids, the arrow between the ellipses represents the Mahalanobis distance between the two centroids. Each plot includes the univariate distributions for the two groups and Cohen's  $d$  between the group means. Overall correlation between the scales is .15, the pooled within group correlation is .45.  $D$  = Mahalanobis distance.

**Figure 4**  
*Plots of the Gruber et al. (2020) Masculine and Feminine Scales of Personality, Cognition, and Interests and Activities*

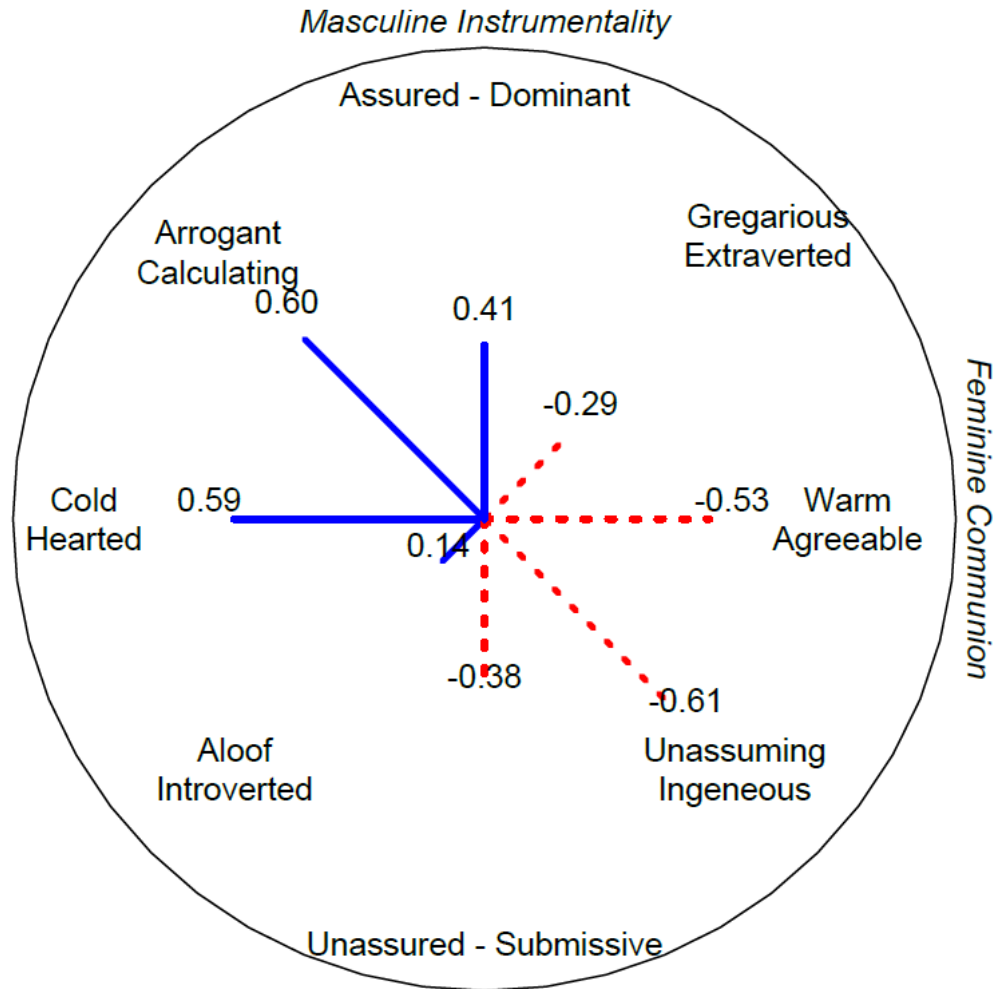


*Note:* The 3 subdomains and overall scores of the Gruber et al. (2020) data set for males (blue) and females (red). The scatter plots show the individual participants, the ellipses reflect one standard deviation from the group centroids, the arrow between the ellipses represents the Mahalanobis distance between the two centroids. Each plot includes the univariate distributions for the two groups and Cohen's  $d$  between the group means. The pooled within group correlations are  $-.16$ ,  $.04$ ,  $.10$  and  $-.05$  for the four panels.  $D = \text{Mahalanobis distance}$ .



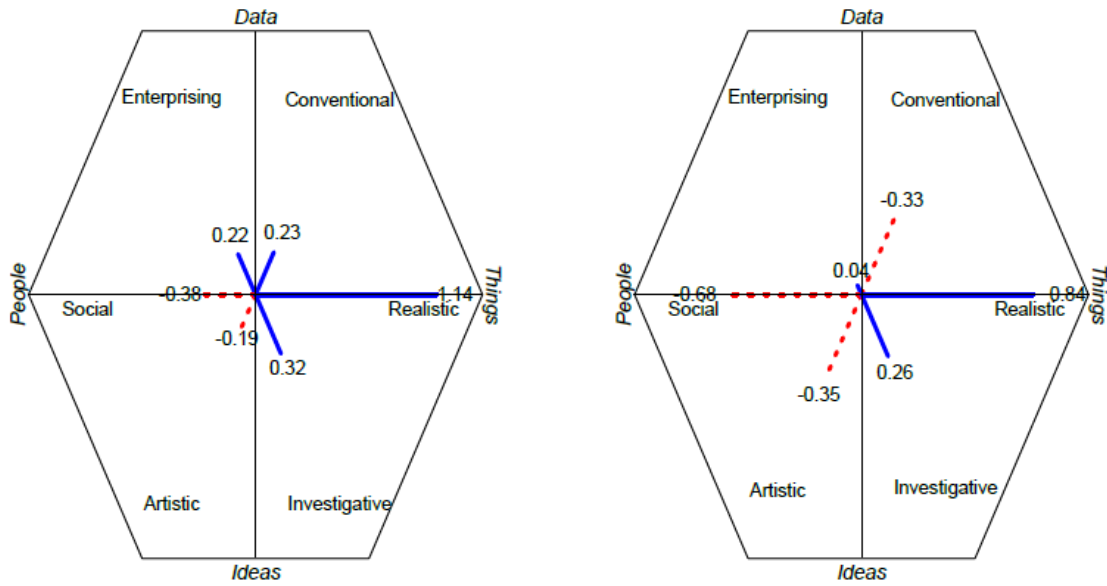
**Figure 5**

**Meta-Analysis of Sex/Gender Differences in Interpersonal Circumplex (Lippa, 2001)**



*Note.* Mean effect sizes (*d*) on the dimensions of the interpersonal circumplex from Lippa (2001) meta-analysis of five studies. Blue lines indicate effects in male direction, and red dotted lines indicate effects in female direction.

**Figure 6**  
*Holland’s Measures of Vocational Interests*



*Note:* Six dimensions of vocational interests organized in the Holland (1997) model. The data on the left are from Su et al. (2009) and on the right are from Morris (2006). Blue lines indicate effects in male direction, and red dotted lines indicate effects in female direction. The labels of the two axes (People vs. Things and Ideas vs. Data) are from Prediger (1982).

## Appendix

### Derivation of Equation for Predicting Scale Validity from Item Characteristics

The benefit of aggregating items to form more reliable composites has been known since Spearman (1904) and thoughtfully reviewed by Epstein (1983). Unfortunately, most interpretations of aggregation emphasize the increase in reliability due to adding more items and assume that validity increases in parallel. This is not the case. Although conventional measures of internal consistency (e.g.,  $\alpha$ ) increase as a function of the number of items in a domain ( $k$ ) and the average correlation within that domain ( $\bar{r}_x$ )<sup>1</sup> the aggregated validity ( $r_{yx}$ ) increases as a function of the number of items, the average item validity ( $\bar{r}_y$ ), and the average correlation of the predicting items ( $\bar{r}_x$ ). Any correlation between two variables is just their covariance divided by the square root of the product of their variances. In the case of predicting a criterion from an aggregation of items, the covariance will be the sum of the individual predictor x criterion covariance ( $\sum r_{y_i}$ ); the variance of the predictor is the sum of the interitem variances and covariances ( $\sum \sum \sigma_{ij}$ ). In the case of standardized predictors (i.e. correlations), the covariance with the criterion will be the number of items x the average item validity ( $k\bar{r}_y$ ); the variance of the predictor is the sum of the number of items ( $k$ ) and the  $k * (k-1)$  intercorrelations ( $k + k * (k - 1)\bar{r}_x$ ). Equation 1 is the result of replacing the sums by the products of averages and the number of items. For a similar derivation see Equation 4, Chapter 9 of Gulliksen (1950).

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<sup>1</sup>This is the well known generalization of the Spearman Brown formula  $r_{xx} = 1 - \frac{\sigma_e^2}{\sigma_x^2} = \alpha = \frac{k}{k-1} \frac{\sigma_x^2 - \sum(\sigma_i^2)}{\sigma_x^2}$  for  $\tau$  equivalent items (Cronbach, 1951; Guttman, 1945).

$$r_{yx_k} = \frac{k\bar{r}_y}{\sigma_x} = \frac{k\bar{r}_y}{\sqrt{k + k * (k - 1)\bar{r}_x}}. \quad (1)$$

If the predicting items all come from the same domain, then  $r_{yx}$  increases with the number of items. But, if the aggregation is taken across different domains, then the aggregated prediction can be much larger than that from any single domain due to the decrease in the average correlation of the prediction set. Thus, as  $k$  grows, the limit of the validity is  $r_{yx_\infty} = \frac{r_y}{\sqrt{r_x}}$ .

In the case of predicting gender/sex differences, scales coded for Masculine or Feminine aspects predict gender/sex as the number of items increases. But forming composite M+F scales increases this effect beyond what would be expected by mere addition of items. Because of the independence of the M and F scales, their composite is a much stronger predictor than either scale by itself. We consider this effect for two different data sets .