Self-Monitoring and the Metatraits

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STRUCTURED ABSTRACT

Objective

Prior attempts at locating self-monitoring within general taxonomies of personality traits have largely proved unsuccessful. However, past research has typically neglected 1) the bi-dimensionality of the Self-Monitoring Scale, and 2) the hierarchical nature of personality. The objective of this study was to test hypotheses that the two self-monitoring factors are located at the level of the metatraits.

Method

Using data from two large multi-informant samples, one community (Sample 1: $N = 522$, $M_{age} = 51.26$, 61% Female; $N_{Peers} = 1{,}551$, $M_{age} = 48.61$, 37% Female) and one online (Sample 2: $N = 3{,}726$, $M_{age} = 24.89$, 59% Female; $N_{Peers} = 17{,}868$, $M_{age} = 26.23$, 64% Female), confirmatory factor analysis was used to test hypotheses.

Results

Results confirmed hypotheses that *acquisitive* self-monitoring would have a strong positive relation to metatrait Plasticity, whereas *protective* self-monitoring would have a moderate negative relation to metatrait Stability. In both samples, constraining the correlation between acquisitive self-monitoring and Plasticity to unity did not alter model fit indices, indicating that the two putatively distinct constructs are identical.

Conclusions

Findings have wide-ranging implications, including integration of the construct of self-monitoring into the mainstream of personality research, as the latter moves toward the development of broad explanatory theories.

Keywords: self-monitoring, metatraits, higher order factors, Stability, Plasticity

Self-Monitoring and the Metatraits

A central goal of personality psychology is the development of a comprehensive yet parsimonious taxonomy of personality. The Five-Factor Model (FFM), or Big Five, constitutes the most prominent and widely used taxonomy of personality traits (John, Naumann, & Soto, 2008). The model posits that individuals differ in dispositional traits along five major dimensions: Extraversion, Openness/Intellect, Emotional Stability, Agreeableness, and Conscientiousness. The five factors have emerged across sexes, ages, languages, cultures, inventories, and raters (Connelly & Ones, 2010; Dilchert, Ones, Van Rooy, & Viswesvaran, 2006; McCrae &Costa, 1987, 1997), indicating the robustness and generalizability of the Big Five. Crucially, the FFM encompasses more than five constructs; hierarchy and an absence of simple structure are intrinsic and pervasive features of the trait taxonomy (Markon, 2009). Some traits are located above the Big Five (e.g., DeYoung, 2006; Digman, 1997), and more are located below (e.g., DeYoung, Quility, & Peterson, 2007). Still other traits cannot be clearly assigned to a single Big Five domain but can nonetheless be located as compound traits, falling within multiple domains (Connelly, Ones, Davies, & Birkland, 2013; Hough & Ones, 2001). The resulting multi-level taxonomy is both more accurate and more comprehensive than a merely one- or two-level system, features that may enable the integration of constructs that, historically, have been poorly represented in the FFM. As personality psychology evolves beyond merely descriptive models toward the development of explanatory theories centering on the Big Five (Denissen & Penke, 2008; DeYoung, 2010a, 2013, 2014; Nettle, 2006; Van Egeren, 2009), it becomes increasingly important to reconcile and integrate constructs developed using different models. One such construct is self-monitoring.

For four decades, self-monitoring (Snyder, 1974) has been a major construct of interest in the psychological literature; the seminal publication has 3,100+ citations (GoogleScholar citation counter, December, 2014). Self-monitoring concerns individual differences in the monitoring and regulation of expressive behaviors and public appearances (Snyder, 1987). Frequently dichotomized in both theory and analysis, *high* self-monitors are particularly sensitive to situational contexts and are willing and able to modify their expressive behavior to fit a given situation or role. In contrast, *low* self-monitors are less responsive to social contexts, typically acting in ways that are congruent with their internal attitudes and dispositions (Fuglestad & Snyder, 2010). Taxometric evidence provided support for the existence of high and low self-monitors as distinct naturally occurring classes of individuals (Gangestad & Snyder, 1985), but a recent study employing updated taxometric methods failed to replicate the taxonic finding in both the original sample, as well as a second data set (Wilmot, 2014). Nonetheless, self-monitoring remains just as interesting a construct if, like most traits, it exists as a continuous dimension rather than a taxon.

Locating SM in the FFM

Prior findings are equivocal concerning the location of self-monitoring within the FFM. Critics provide evidence that self-monitoring demonstrates little incremental validity over measures of Extraversion (John, Briggs, & Klohnen, 1996), whereas proponents dispute this "self-monitoring as Extraversion hypothesis" (Gangestad & Snyder, 2000, p. 534). In an attempt to bring clarity to controversy, Barrick, Parks, and Mount (2005) reported estimates from an unpublished meta-analysis of Schleicher and Day (2002) concerning relations of self-monitoring to the Big Five. Results indicated that self-monitoring had a moderate positive correlation with Extraversion (ρ = .44), but negligible correlations with Emotional Stability, Agreeableness, and Conscientiousness ($\rho = -$ .02, .05, and -.03, respectively). The Openness/Intellect correlation was not reported. In light of these meta-analytic findings, Barrick and colleagues inferred that self-monitoring "is not well represented in the FFM" (2005, p. 748).

This meta-analytic conclusion is potentially flawed; the difficulty of locating self-monitoring within the FFM may be due to methodological problems rather than to substantive differences in the constructs. Problems include competing operationalizations of the self-monitoring construct (Lennox & Wolfe, 1984), as well as multidimensionality in both the original and revised versions of the Self-Monitoring Scale (Briggs, Cheek, & Buss, 1980; Snyder, 1974; SMS; Snyder & Gangestad, 1986; SMS-R). Concerning the problem of multidimensionality, Briggs and Cheek (1988) reported that the SMS-R contained two major factors, which were virtually orthogonal (r = .08). These two factors had divergent—even competing—nomological networks in relation to various measures of personality; the former was positively related to social "approach" measures (e.g., social potency), whereas the latter was positively related to social "avoidance" measures (e.g., shyness). Relations bore striking parallels to Arkin's two basic styles of self-presentation (1981). Arkin theorized that the desire for social approval underlies the preponderance of interactional goals (1981, p. 312). However, the pursuit of social approval and, alternatively, the avoidance of social disapproval represent two distinct self-presentational strategies, which were termed *acquisitive* and *protective*, respectively. Based on these empirical parallels, the acquisitive and protective labels were appended to the two self-monitoring factors (Lennox, 1988), and we also employ these labels. Critically, the discrepant relations of the *two* self-monitoring factors become obscured by combining them to compute *one* full-scale self-monitoring score. Consequently, researchers have advocated the use of a bivariate model and a corresponding subscale-scoring scheme (Briggs & Cheek, 1988; see also John et al., 1996), a recommendation contested by Gangestad and Snyder based on the argument that the

SMS-R is functionally univariate. That is, full-scale scores are much more strongly related to the large first (acquisitive) factor than to the smaller second (protective) factor, which accounts for relatively little variance in full-scale scores (Gangestad & Snyder, 1991, 2000).

Unfortunately, subscale differences were not reported by Barrick and colleagues (2005) as a possible moderator of meta-analytic findings. Nevertheless, an emerging body of cross-cultural findings indicates that a bivariate model of self-monitoring merits reconsideration. In five translations of the SMS-R, a two factor solution similar to that of Briggs and Cheek (1988) was found in German (Nowak & Kammer, 1987), Kenyan (Kodero, 1991), Portuguese (Neto, 1993), Spanish (Avia, Sanchez-Bernardos, Sanz, Carrillo, & Rojo, 1998), and Israeli samples (Bachner-Melman, Zohar, Kremer, Komer, Blank, Golan, & Ebstein, 2009). Also replicated were the divergent nomological networks across factors, in relation to both the Big Five and their facets (Avia et al., 1998; Wolf, Spinath, Riemann, & Angleitner, 2009). Although researchers have noted these divergent networks as a cause for either caution (Bachner-Melman et al., 1998) or criticism (Avia et al., 1998) in the use of full-scale scores, all overlooked a distinctive pattern of interrelations. Namely, the acquisitive and protective self-monitoring factors bear a striking resemblance to another bivariate structure: the higher-order factors of the FFM. Acquisitive self-monitoring was correlated relatively strongly with both Extraversion and Openness/Intellect and almost all of their facets, whereas protective self-monitoring was negatively correlated, if somewhat more weakly, with Neuroticism, Agreeableness, and Conscientiousness and almost all of their facets (Avia et al., 1998; Wolf et al., 2009).

SM and the Metatraits: Theoretical and Empirical Linkages

The higher-order factors, or metatraits, are substantive traits that account for much of the shared variance among the Big Five dimensions (DeYoung, 2006; Digman, 1997; Olson, 2005).

The first metatrait, variously labeled Alpha, Self-Control, or Stability is composed of the shared variance of Emotional Stability (Neuroticism reversed), Conscientiousness, and Agreeableness and appears to reflect the stable maintenance of goal-directed psychological functioning (DeYoung, 2014). The second metatrait, labeled Beta, Engagement, or Plasticity is composed of the shared variance of Extraversion and Openness/Intellect, and appears to reflect exploration and engagement with novel information and opportunities (DeYoung, 2014). The metatraits have been linked to biological substrates and associated behaviors (DeYoung & Gray, 2009; DeYoung, Peterson, & Higgins, 2002). Plasticity was linked to the neurotransmitter dopamine and to behavioral engagement, and Stability to serotonin and behavioral restraint (Hirsh, DeYoung, & Peterson, 2009). As another indication of their importance, the metatraits are similar to the two factors demonstrated by lexical research to constitute the most replicable factor solution across languages, which have been labeled Dynamism and Social Self-Regulation (Saucier, Thalmayer, Payne, Carlson, Sanogo, Ole-Kotikash, … & Zhou, 2014).

The metatraits exhibit notable conceptual linkages to self-monitoring, especially between Plasticity and acquisitive self-monitoring. Previous empirical research indicates that Plasticity is associated with the frequency of behaviors reflecting social engagement (e.g., planning a party, giving a lecture; Hirsh et al., 2009), and items tapping Plasticity are characterized by social skill, social expressivity, and leadership (DeYoung, 2010b). Similarly, quantitative review indicates that self-monitoring is related to expressive control, emotional decoding skill, and leadership emergence (Day, Schleicher, Unkless & Hiller, 2002; Gangestad & Snyder, 2000). Linkages between Stability and protective self-monitoring are somewhat weaker, but noteworthy. Both low Stability and protective self-monitoring were correlated with self-reported alcohol and drug use (Hirsh et al., 2009; Wolfe, Lennox, & Hudiburg, 1983). Moreover, the anxious attention and responsiveness to others associated with protective self-monitoring may partially reflect the behavioral inconsistency and identity confusion characteristic of low Stability (DeYoung, 2010b, 2014; Gangestad & Snyder, 2000).

Stability and Plasticity predict some constructs in opposite directions, and this may shed light on the seemingly unitary functioning of the bi-dimensional SMS-R in relation to certain criteria that appear to be associated with low Stability and high Plasticity, or vice versa (e.g., some attitude-behavior relations; Gangestad & Snyder, 2000). For example, Stability was positively and Plasticity was negatively related to conformity with moral norms in community and undergraduate samples (DeYoung et al., 2002). This parallels Q-sort descriptions of the prototypical low self-monitor that include “is moralistic”, “behaves in an ethically consistent manner”, and “appears straightforward, forthright, and candid” (John et al., 1996, p. 766). As a second example, evidence indicates that high self-monitors were more likely than low self-monitors to have an unrestricted orientation toward sexual relations (i.e., increased number of sexual thoughts, greater frequency of engaging in sex on a single occasion). Further, these effects were similar at the subscale level; that is, despite being virtually orthogonal to one another, indices of acquisitive and protective self-monitoring were each positively and uniquely related to attitudes and behaviors reflecting an unrestricted orientation to sexuality (Snyder, Simpson, & Gangestad, 1986). These results mirror findings that both *low* Stability and *high* Plasticity were independently associated with increased engagement in sexual behaviors (Hirsh et al., 2009). Thus, for certain criteria, the metatraits, in combination, function similarly to the aggregate of the two self-monitoring factors, which may help to explain why the SMS-R sometimes appears to function in a unitary manner, despite its bi-dimensional internal structure (cf. Renner, Laux, Schütz, & Tedeschi, 2004).

Locating SM above the FFM

In summary, convergent cross-cultural findings, as well as conceptual linkages between the metatrait and self-monitoring literatures, provide warrant for the current investigation. Our hypothesis is that self-monitoring is not poorly represented by the FFM framework; instead, it only appears to be so for two reasons: 1) the use of full-scale SMS-R scores, which obscure substantive relations of the two self-monitoring factors to the FFM; and 2) a failure to examine relations at the most appropriate level of the personality hierarchy. We tested this hypothesis in two multi-informant samples. The first was a community sample comprising N = 552 participants whose personalities (Big Five and self-monitoring) were rated by themselves and two or three peers (Big Five only). The second was an online sample comprising N = 3,726 Facebook users whose personalities were likewise rated by themselves and two or more peers. Taking the square root of the mean sample size weighted correlations from two prior studies (i.e., Avia et al., 1998; Wolf et al., 2009), we estimated that acquisitive self-monitoring would have a strong positive relation to metatrait Plasticity ($r \approx .65$), while protective self-monitoring would have a moderate negative relation to metatrait Stability ($r \approx -.45$).

If our hypothesis is supported, the implications are important both for those interested in the nature of self-monitoring and for those interested in personality more generally. Theorizing about self-monitoring has recently explored the motivational foundations of the trait (Fuglestad & Snyder, 2010; Gangestad & Snyder, 2000), linking it to a desire for status. If acquisitive self-monitoring reflects Plasticity, then the drive for status can be partially understood in terms of the more basic dopaminergic mechanisms of exploration and reward seeking that appear to be crucial for Plasticity (DeYoung, 2013). Additionally, the entirety of the self-monitoring literature would become relevant to understanding the consequences of individual differences in Plasticity, thereby greatly expanding the nomological network of the metatraits. Because the majority of variance in SMS-R scores reflects acquisitive self-monitoring, protective self-monitoring has received less theoretical attention. If protective self-monitoring is linked to low Stability, then this could provide a major step toward developing an account of its motivational foundations.

Method

Participants

Sample 1. Participants were 552 members of the Eugene Springfield Community Sample (ESCS; 231 males and 321 females), ranging from 18 to 80 years (M = 51.26, SD = 12.50). Participants were homeowners recruited by mail to complete questionnaires, for payment, over a period of years, beginning in 1994. All education levels were represented, with the average being two years of post-secondary schooling. Most participants self-identified as White (98%). The remainder were Hispanic, Asian American, Native American, or did not report their ethnicity.

For study inclusion, individuals needed to meet three criteria: Complete self-report data was available for 1) the original Self-Monitoring Scale (SMS); 2) the Big Five Inventory (BFI); and 3) BFI ratings of the target were available from two (N = 105) or three informants (N = 447). These 1,551 informants (578 female, 969 male, 4 no sex reported) were spouses, friends, relatives, coworkers, and acquaintances; ages ranged from 6 to 94 years (M = 48.61, SD = 17.80).

Sample 2. Participants were 3,726 Facebook users (2,186 females, 1,340 males, 200 with no sex reported), ranging from 15 to 112 years (M = 24.89, SD = 9.23). Data were obtained from the myPersonality application (Kosinski, Stillwell, & Graepel, 2013). Users of the myPersonality application (www.mypersonality.org) elected to provide research data in exchange for the opportunity to complete assessments and display results on their Facebook profiles. All assessments were administered in English, even in countries where English is not the native language. Racial, ethnic, or educational data were not available. When location data was available (*N* = 3,331), the most common countries of users were the United States (*N* = 2,395, 71.9%) and Great Britain (*N* = 771, 23.1%); the remainder (*N* = 165) resided elsewhere.

Inclusion criteria for Study 2 were essentially identical to Study 1. To be included, complete self-report data was available for 1) the original Self-Monitoring Scale (SMS); 2) the International Personality Item Pool (IPIP) Big Five; and 3) IPIP ratings of the target were available from two or more informants. A total of *N* = 17,868 informant ratings were voluntarily provided by peers on Facebook; the number of target ratings ranged from two to 50 (*M* = 3.80, *SD* = 2.65). Informants ranged in age from 15 to 112 years (*M* = 26.23, *SD* = 8.66), and were 64% female. Similar to target data, informant ratings primarily came from the United States (71.8%) and Great Britain (24.0%); racial, ethnic, or educational information was not reported.

Measures

The original Self-Monitoring Scale (Snyder, 1974) contains 25 items. Sample 1 completed the SMS using a 5-point Likert-type response format (1 = strongly disagree, 5 = strongly agree), while Sample 2 utilized a dichotomous response format (0 = False, 1 = True). Factor analytic evidence indicates that the SMS contains three factors, the corresponding subscales of which were labeled, *Acting*, *Other-Directedness*, and '*Extraversion'* (Briggs et al., 1980). In an effort to remove this multidimensionality, Snyder and Gangestad (1986) eliminated seven items (mostly from the Other-Directedness factor) and published the 18-item Self-Monitoring Scale-Revised (SMS-R). Despite the revision, Briggs and Cheek (1988) reported the presence of two virtually orthogonal major factors in the SMS-R. The first factor (i.e., acquisitive self-monitoring) contained items represented on the previously identified Acting and Extraversion factors; eight items met the pre-determined loading criteria of ≥ .30 in absolute value and were included in the associated subscale, *Public Performing.* The second major factor comprised items remaining from the truncated Other-Directedness factor (i.e., protective self-monitoring); hence, the name of its 5-item subscale: *Abbreviated Other-Directedness*.

John and colleagues criticized the SMS-R, arguing that the scale revision led to a conceptual shift toward extraverted (and away from other-directed) self-presentation (1996, p. 765), and they recommended using the original SMS and scoring the Public Performing and the Other-Directedness subscales separately. Although we concur with this recommendation regarding the Public Performing subscale, a few modifications to their suggested Other-Directedness subscale were warranted. Although 11 items were included in the original 1980 Other-Directedness subscale, three of these items (i.e., SMS 3, 15, and 17) failed to meet the predetermined loading criteria of $r \geq .30$ in absolute value in the subsequent 1988 factor analytic investigation (Briggs & Cheek, 1988). Our aim was to examine the utility of the bivariate scoring scheme by using only the strongest and most robust indicators of both self-monitoring factors. As a result, in a strategy that paralleled the approach used to select items for the Public Performing subscale, we chose to include any Other-Directedness item (pre- or post-scale revision) that met the loading criteria of $r \geq .30$ in both the 1980 and 1988 factor analytic studies. In total, eight items[2] met this criterion: the five Abbreviated Other-Directedness subscale items that remained after the scale revision, and three items (i.e., SMS 2, 7, and 19) that had been eliminated during the revision process.

In summary, 15 SMS items were selected *a priori* and in accordance with the bivariate model of John et al (1996) for use in our investigation: seven items uniquely associated with the acquisitive self-monitoring factor, six items uniquely associated with the protective self-

[2] The eight items are the same as those reported in the bottom half of Table 3 by Briggs and Cheek (1988, p. 666).

monitoring factor, and two items cross-loading on both factors. It should be noted that the purpose of our study was *not* to fit a confirmatory factor analytic model to either the full SMS or the SMS-R; for a review of such studies, the reader is directed to Hoyle and Lennox (1991). Estimates of internal consistency for the acquisitive self-monitoring items (α = .80 and .70) were acceptable in both data sets, while reliabilities for protective self-monitoring were lower (α = .64 and .59). An illustrative acquisitive self-monitoring item is: "I would probably make a good actor" (SMS 8); an example protective self-monitoring item is: "In different situations and with different people, I often act like very different persons" (SMS 13).

The BFI (John & Srivastava, 1999) is a widely used measure of the Big Five. The scale contains 44 descriptive items, with each trait domain indicated by 8 to 10 items. During the summer of 1998, the measure was administered to Study 1 participants and to peers who knew the participants well and were asked to rate them. A common 5-point Likert-type response format (1 = strongly disagree, 5 = strongly agree) was utilized. Estimates of internal consistency were in the desirable range (α = .80 to .87), and inter-rater reliabilities between self-ratings and mean informant ratings were also adequate (r = .44 to .64).

The IPIP (Goldberg, 1999) is a widely used pool of personality items, which includes standard Big Five measures. Big Five measures of various lengths were utilized in Study 2, ranging from a 20-item "mini" scale to the standard 100-item version. The reason for this variation was that users of the myPersonality application could decide, in advance, the length of questionnaire they wanted to take, or could elect to complete additional items in blocks of 10 until they finished all 100 items. Because respondents took the inventory to get feedback, they tended to be motivated to complete longer versions; indeed, N = 3,184 (85.4%) completed the full 100-item measure. Informants who were friends on Facebook voluntarily provided ratings of the target, and rated two randomly administered items per domain, for a total of 10 items. A 5-point Likert-type response format (1 = strongly disagree, 5 = strongly agree) was utilized for self- and peer-ratings alike. Reported (http://mypersonality.org) internal consistency estimates for the 100-item version are excellent (α = .85 to .93), and part-whole correlations between the 20 and 100-item scales are also strong (r = .77 to .91). The inter-rater reliabilities between self- and mean informant-ratings were in the acceptable range (r = .35 to .46).

Evidence indicates that the metatraits are substantively real, but their estimation is somewhat inflated by evaluative biases in self-report ratings (Chang, Connelly, & Geeza, 2012; DeYoung, 2006). Moreover, meta-analytic evidence indicates that peer-ratings contribute incremental predictive validity over and above self-ratings (Connelly & Ones, 2010). Therefore, multi-informant data should provide a more accurate and representative assessment than self-report ratings alone. To compute multi-informant scores, we first calculated the average item rating (on a scale of 1 to 5) for each Big Five domain for self-ratings and informant-ratings separately. Next, because the number of informant-ratings differed across samples, we used the mean peer-rating to facilitate the comparability of results across data sets. Finally, we averaged self-ratings and mean peer-ratings for each Big Five dimension. Thus, self-ratings and mean informant-ratings each contributed 50% to the final multi-informant scale scores. The advantage of this arithmetic approach is that it captures both common and unique valid variance associated with the different perspectives on the participants' personalities.

Analyses

We used both parallel analysis and Velicer's minimum average partial (MAP) test (O'Connor, 2000; Velicer, 1975) to determine the number of factors present in the 15 self-monitoring items in the two data sets. Both tests indicated the presence of two factors in both data sets. Principal axis factoring was used to extract two unrotated factors; all factor loadings are reported in Table 1. Respective eigenvalues for factors 1 and 2 were λ = 3.51 and 2.50 for Sample 1, and λ = 2.72 and 2.22 for Sample 2. Next, we used Tucker's (1951) coefficient of congruence to quantify the similarity between the first and second unrotated factors across data sets. Results indicated that the coefficients of congruence were very strong (r_c = .988 and .980), with coefficients >.95 being indicative of replication (Lorenzo-Seva & ten Berge, 2006). Consequently, we are confident that the same two factors were measured across studies. Subscales corresponding to the two factors were subsequently computed to calculate descriptive statistics.

[Insert Table 1 about here.]

Descriptive statistics for all variables for Samples 1 and 2 are provided in Table 2. Across samples, results indicate that acquisitive self-monitoring had strong relations to Extraversion (r_{S1} = .57, r_{S2} = .51) and moderate relations to Openness/Intellect (r_{S1} = .36, r_{S2} = .19); thus, zero-order correlations to the constituent traits of Plasticity provide evidence for the hypothesized strong positive relation of the metatrait to acquisitive self-monitoring. Additionally, results indicate that protective self-monitoring had small negative relations to Emotional Stability (r_{S1} = -.20, r_{S2} = -.24), Agreeableness (r_{S1} = -.17, r_{S2} = -.11), and Conscientiousness (r_{S1}= -.26, r_{S2} = -.20), providing evidence for the hypothesized moderate negative relation to metatrait Stability.

Next, a confirmatory factor analytic model (Figure 1) was used to test predictions about the relations of acquisitive and protective self-monitoring to metatraits Plasticity and Stability. The model was analyzed using AMOS version 22.0.0 (Arbuckle, 2012) with maximum likelihood estimation of the full covariance matrix. The arithmetic mean of self-ratings and mean informant-ratings of the Big Five domain scores were used as manifest indicators of the two latent metatraits. Public Performing subscale items (SMS 1, 5, 8, 12, 18, 20, and 22) were used to estimate the acquisitive self-monitoring factor, and Other-Directedness items (SMS 2, 7, 13, 16, 19, and 25) were used to estimate the protective factor. Due to their history of cross-loading (cf. Briggs & Cheek, 1988, p. 664), paths to items 6 and 23 were freed to load on both latent self-monitoring variables. All item numbers correspond to the order as presented in the original 25-item Self-Monitoring Scale (Snyder, 1974).

It is relevant to note that differences in measurement levels exist across indicators in the present measurement model. That is, for each of the Big Five trait domains, multi-informant *scale* scores were used to estimate the metatraits; in contrast, 15 self-report *item* responses were used to estimate the latent self-monitoring factors. As a result, responses to self-monitoring indicators were less reliable and more likely to have uniquenesses (i.e., variances not accounted for by latent variables) attributable to measurement artifacts. Consequently, we included one *a priori* residual correlation between items 8 and 18; these items are nearly synonymous with one another, and have been highly correlated in other samples (e.g., r = .54 in Briggs & Cheek, 1988).

[Insert Table 2 about here.]

Results

Structural hypotheses were tested according to the model in Figure 1. Plasticity had a stronger than expected relation to acquisitive self-monitoring (r_{S1} = .99, r_{S2} = .93), whereas the relation between Stability and protective self-monitoring was moderately negative, as hypothesized (r_{S1} = -.42, r_{S2} = -.44). Among other relations, acquisitive self-monitoring was unrelated to protective self-monitoring in both samples (r_{S1} = .05, r_{S2} = -.02), and its correlation with Stability was nil in Sample 1 (r_{S1} = -.02), but slightly positive in Sample 2 (r_{S2} = .13). The relation of Plasticity to protective self-monitoring was moderately negative and comparable across samples (r_{S1} = -.33, r_{S2} = -.30). Finally, the relation between Plasticity and Stability was larger in Sample 2 than in Sample 1 (r_{S1} = .32 vs. r_{S2} = .58), which paralleled the relatively larger correlation between Extraversion and Emotional Stability in Sample 2 (r = .34). This inflated value was probably attributable to the abbreviated nature of the peer-report IPIP scales (10-items total) and, thus, is an artifact of lower-quality measurement, rather than a substantive difference.

[Insert Figure 1 about here.]

Table 3 provides the chi-square statistic for lack-of-fit between the predicted and observed covariance matrices, and degrees of freedom. Additionally, two indices of relative fit, the Tucker–Lewis index (TLI) and the comparative fit index (CFI), as well as two indices of absolute fit, the root-mean-square error of approximation (RMSEA) and the standardized root-mean-square residual (SRMR), are also provided. Relative fit indices compare the theoretical model to an independence (null) model wherein only variances are modeled; absolute indices, in contrast, do not impose a baseline model. Relative indices address the question, How well does the theoretical model fit compared to other possible alternatives? Absolute indices provide a direct test of the size of residuals, addressing the question, Is the unexplained variance appreciable? Concerning rules-of-thumb for fit, a large chi-square value does not necessarily indicate poor fit, because the chi-square statistic is sensitive to sample size; consequently, it will frequently be statistically significant even for good models (Kline, 2005). For relative fit indices, TLI and CFI values > .90 typically indicate adequate fit, and values of > .95 are indicative of close fit. For absolute fit indices, RMSEA and SRMR values < .08 indicate acceptable fit, and values with 95% confidence intervals overlapping .05 indicate excellent fit (Kline, 2005).

[Insert Table 3 about here.]

Fit indices indicate that Model 1 had a suboptimal relative fit to the data in Sample 1 and 2 for both the TLI (.849 and .819) and CFI (.872 and .847), but the RMSEA (.059 and .052) and the SRMR (.058 and .049) indicated that the absolute fit was excellent on both accounts (see Table 3). The discrepancy between fit indices can be understood when one recalls that fit indices estimate fit in two models. Namely, the relations among the manifest indicators of the latent factors (i.e., the *measurement* model) and relations among the latent factors themselves (i.e., the *structural* model). In the present analysis, the structural model is just-identified—that is, all parameters among latent variables are estimated. The fit of the structural model, therefore, is optimal. The remaining lack of fit then can all be attributable to the measurement model, which, as mentioned earlier, is limited by the constraint of using single items as indicators of self-monitoring factors. Fit was improved if we allowed additional correlated residuals among some self-monitoring items based on modification indices (e.g., 8 and 20; 13 and 16); however, doing so did not substantively change associations among latent variables. Because both the RMSEA and SRMR indicated excellent fit, and because our substantive theoretical question was with the structural model, we resisted the temptation to report additional correlated residuals so as to avoid overfitting the model. Finally, it should be noted that suboptimal relative fit values are consistent with prior CFA investigations of the SMS (cf. Hoyle & Lennox, 1991).

In light of the exceptionally strong relation between the latent Plasticity and acquisitive self-monitoring factors, we estimated a second model that constrained their correlation to equal 1.00. This constraint formally tests the hypothesis that the two putatively different variables are actually one and the same. Across both samples, fit indices for the unconstrained and constrained models were virtually identical (see Table 3). Since parsimony favors the simpler of the two equally fitting models, this evidence indicates that acquisitive self-monitoring and metatrait

Plasticity are equivalent constructs.

Discussion

Our results provide strong evidence that self-monitoring is not poorly represented by the FFM framework; rather, it only appears that way due to the computation of full-scale scores from two largely orthogonal factors, and the failure to examine relations at the correct level of the personality hierarchy. In two sizeable multi-informant samples, confirmatory factor analysis was used to test hypotheses that acquisitive and protective self-monitoring would be located above the Big Five domains, at the level of the metatraits. Results confirmed the hypothesis that acquisitive self-monitoring would have a strong positive relation to metatrait Plasticity, whereas protective self-monitoring would have a moderate negative relation to metatrait Stability.

Interestingly, the degree of association between acquisitive self-monitoring and Plasticity was considerably stronger than anticipated. Indeed, in both samples, goodness-of-fit tests between the unconstrained and constrained models indicated that constraining the correlation between acquisitive self-monitoring and Plasticity to equal 1.00 did not alter model fit indices. This finding was common across two large samples, each of which utilized different data collection methods (in-person versus online), different Big Five measures (BFI versus IPIP), and different response formats for the SMS (polytomous versus dichotomous). The finding is particularly impressive given that the Big Five were measured using both self- and peer-reports, whereas self-monitoring was only self-reported. Based on these results, we can confidently conclude that acquisitive self-monitoring is *equivalent* to metatrait Plasticity—that is, the shared variance of Extraversion and Openness/Intellect. Although the relation of protective self-monitoring to Stability was much less spectacular, the finding nevertheless contributes to explicating the nature of this independent source of variance in the SMS.

The current findings have implications for personality structure, in general, and self-monitoring, in specific. First, concerning personality structure, results are consistent with emerging findings that hierarchy and complex structure are intrinsic and pervasive features of the taxonomy of personality traits (Markon, 2009). Although the Big Five traits may provide the FFM with its namesake, researchers should not assume that the model begins and ends with five dimensions. Evidence of multiple levels of traits should encourage future efforts to integrate other "jangling" constructs into the FFM framework by examining relations across multiple levels of the hierarchy. Additionally, validation efforts for new measures should demonstrate convergent and/or discriminant validity across multiple levels of the hierarchy of traits.

Second, results provide additional evidence that metatrait research is a substantive area of inquiry that merits serious consideration. Moreover, somewhat serendipitously, the present findings indicate that metatrait research may be more developed than previously thought. Indeed, the self-monitoring literature may provide a fully-grown nomological network for Plasticity. Given that acquisitive self-monitoring and Plasticity are identical, it may be possible to integrate the voluminous self-monitoring literature into the broader FFM literature, to their mutual enrichment. A prime example of enrichment potential is evidence that status concerns are central to self-monitoring processes across life domains (Day et al., 2002; Fuglestad & Snyder, 2010). In their review, Fuglestad and Snyder (2010) suggest that high self-monitors have a stronger status motive, are more accurate in perceptions of and responsivity to status, and are more able to cultivate status within social hierarchies. High self-monitors cultivate this status not only by being assertive and self-enhancing, but also "by getting along with others, being helpful to others, occupying boundary spanning positions in social and work networks, and counteracting negative expectations of others in occupational and evaluative settings" (Fuglestad and Snyder, 2010, p.

1038). Mirroring these findings, evidence indicates that the strongest behavioral correlates of Plasticity were related to positive interpersonal engagement, such as being consulted for help or advice concerning personal problems, and planning a party (Hirsh et al., 2009). Although researchers have yet to investigate relations between Plasticity and status concerns explicitly, agency and assertiveness, traits linked to the “Status” dimension of the interpersonal circumplex, appear to be core manifestations of Plasticity (DeYoung, 2013). In short, efforts to integrate the self-monitoring and FFM literatures promise to be scientifically generative, providing new perspectives on old findings, and stimulating fresh theory and hypotheses.

Implications for Measurement

Although the possibilities of integration are encouraging, immediate wholesale importation of the self-monitoring literature into the FFM would be premature for three reasons. First, although Plasticity and acquisitive self-monitoring factors appear to be isomorphic, and although the relation of acquisitive self-monitoring to the SMS-R (r = .90 and .87) was nearly seven times larger than its correlation to protective self-monitoring (r = .36 and .32), nevertheless, all empirical findings using full-scale scores remain contaminated, to a degree, by the smaller, protective self-monitoring factor.

Second, statistical artifacts present in early self-monitoring research (e.g., dichotomization into high/low self-monitor groups, range enhancement by extreme-group selection) may have also biased published parameter estimates (Hunter & Schmidt, 2004). Historically, the use of full-scale SMS-R scores and the aforementioned measurement practices have been justified based on convention, taxometric evidence, and the paucity of variance contributed by the second factor (Gangestad & Snyder, 1985; 1991). However, future researchers may need to reconsider the taxonic justification. Using both the sample from the original taxometric analysis study (*N* = 1,918) and a replication sample (*N* = 2,951), Wilmot (2014) retested the latent structure of self-monitoring using contemporary taxometric procedures. Results failed to support the prior taxonic claim; to the contrary, convergent findings across multiple taxometric procedures and both samples provided strong evidence that the latent structure of self-monitoring is dimensional rather than categorical. Consequently, researchers may benefit from decoupling acquisitive and protective self-monitoring, and by using a scoring scheme, such as the one presented herein or by John et al. (1996), that reflects the latent bivariate dimensional structure of the scale. Given that a prominent argument for the utility of the full-scale scores has been that they are so strongly correlated with the acquisitive self-monitoring factor (Gangestad & Snyder, 1991), there is no logical reason not to use the shorter and psychometrically cleaner subscale instead of full-scale scores, in future research. Doing so need not cause any problem for the theoretical advances already made for acquisitive self-monitoring (e.g., Fuglestad & Snyder, 2010), and it opens the way toward a more thorough investigation of protective self-monitoring as an independent construct. Additionally, researchers may benefit from revisiting archival data sets and reanalyzing them using a bivariate scoring scheme to isolate the sources of predictive variance. At a minimum, future researchers should report subscale results alongside full-scale findings (Snyder & Gangestad, 1986). Such procedures would contribute much to literature integration.

Third, there is a competing conceptualization of self-monitoring, which explicitly defined the construct as bi-dimensional in nature (Lennox & Wolfe, 1984). Acquisitive self-monitoring was operationalized in the 13-item Revised Self-Monitoring Scale (RSMS), and protective self-monitoring was measured via the 20-item Concern for Appropriateness Scale; the RSMS and CAS contain two subscales each (Lennox & Wolfe, 1984). However, surprisingly little research has examined the interrelations between these two alternative operationalizations of the self-monitoring construct. The most extensive investigation to date indicates only minimal overlap across operationalizations (Shuptrine, Bearden, & Teel, 1990). What is more, to our knowledge, there are no published studies that report interrelations at the subscale level (i.e., acquisitive self-monitoring as measured by Snyder's scale and that of Lennox and Wolfe). Thus, the degree to which the findings of this present study apply to the scales of Lennox and Wolfe remains largely unknown and a subject for future investigation. A cumulative examination of the interrelations across alternative operationalizations would provide a further desirable step toward integration.

In summary, a number of methodological, conceptual, and empirical obstacles remain to be surmounted before the literatures can be fully linked. A promising investigation would be a meticulous meta-analysis of the self-monitoring construct using the bi-dimensional model; such a review would need to examine key moderators (e.g., subscales) and correct for the biasing effects of statistical artifacts that were often present in past self-monitoring research (i.e., dichotomization). In addition, this review would need to examine the nature of relations between the different operationalizations of the self-monitoring construct (including interrelations at the subscale level), expand upon previous reviews (Barrick et al., 2005; Day et al., 2002; Gangestad & Snyder, 2000), and examine relations to theoretically relevant behaviors and psychological correlates, including the Big Five at various levels of the trait hierarchy, as well as important life and work-related outcomes. We leave that considerable task to future researchers.

Implications for Theory

Among the most important aspects of our results is what they suggest about the motivational underpinnings of both acquisitive and protective self-monitoring. Knowing that acquisitive self-monitoring is Plasticity and that protective self-monitoring is substantially negatively related to Stability provides a valuable opportunity to enrich our theoretical understanding of self-monitoring, by bringing to bear existing theory about the metratraits (DeYoung, 2013, 2014; DeYoung et al., 2002; Hirsh et al., 2009).

Plasticity reflects individual differences in the basic tendency toward exploration and engagement with the positive possibilities inherent in any unpredictable or complex situation. It encompasses status-related traits because, for a species that exists in social hierarchies, status is functionally equivalent to the ability to secure resources and accomplish goals. The motivation to seek both rewards and information is governed by the neurotransmitter dopamine, and considerable evidence suggests that variation in dopaminergic function is at least partially responsible for variation in Plasticity, with dopaminergic response to possible rewards being related to Extraversion, and dopaminergic response to the possibility of acquiring information to Openness/Intellect (DeYoung, 2013). People high in acquisitive self-monitoring, then, are presumably motivated to pay attention to the influence they have on others, and to adjust their social behavior flexibly, in part because their higher levels of dopamine make them more strongly motivated to pursue their goals. This is entirely consistent with the suggestion that high self-monitors engage in impression management aimed at "bringing the behavior of others in line with one's own agenda" and "getting what one desires" (Fuglestad & Snyder, 2010, p. 1032). Plasticity and, thus, acquisitive self-monitoring involve flexibly and voluntarily adjusting one's strategic self-presentation in order to pursue one's goals (DeYoung, 2010b); dopamine increases behavioral and cognitive flexibility as well as desire (DeYoung, 2013). People high in acquisitive self-monitoring are not only concerned and motivated by status, they are more broadly concerned with their ability to pursue positive possibilities, achieve their goals, and accomplish their ambitious agendas.

People low in Plasticity, and, thus, in acquisitive self-monitoring, are both less ambitious and less willing and able to adjust their behaviors in the pursuit of their goals. This may help to explain why they seek out situations in which participants are relatively equal in status, rendering bold engagement with the social milieu less necessary (Fuglestad & Snyder, 2010). Presumably, low Plasticity individuals do not have a level of dopaminergic response to possibility that is sufficiently high to drive them to pursue ambitious agendas with vigor and flexibility. They neither desire nor find it easy to adjust their social behavior strategically.

Our finding that acquisitive self-monitoring is equivalent to Plasticity broadens and deepens current theory about self-monitoring without radically altering it. Where we hope to alter current theoretical approaches more dramatically is in our call to pay more attention to protective self-monitoring as partially a manifestation of low Stability. Recognizing protective self-monitoring as a construct independent of acquisitive self-monitoring salvages important conceptual aspects of self-monitoring that have been excluded because they do not reflect the dominant theory, which primarily applies to acquisitive self-monitoring. Instead of asserting that self-monitoring does not involve "vigilant attention and responsivity to others," or "social anxiety, concern for negative social evaluation, and appeasing social behaviors" (Fuglestad & Snyder, 2010, p. 1032; see also Gangestad & Snyder, 2000), we can instead identify these tendencies as features of protective self-monitoring. They may be unrelated to acquisitive self-monitoring, but we suggest that people may be concerned about the way others react to them not only because they are high in Plasticity, but also because they are low in Stability.

To be low in Stability is to have difficulty controlling impulses and maintaining stable goal-directed functioning. Evidence suggests that Stability may be due in large part to individual differences in serotonin function (DeYoung, 2010a; DeYoung et al., 2002). Serotonin appears to be crucial both for suppressing emotional behaviors that stem from low-level, phylogenetically ancient brain systems responsible for appetitive impulses and fight-or-flight impulses (Gray & McNaughton, 2000), and for maintaining determination and energy to carry out behaviors appropriate for one's non-immediate goals (Carver, Johnson, & Joorman, 2008). Low Stability is associated with impulsivity and lack of self-control, with various forms of distress, and, perhaps most relevantly, with a shaky sense of identity, direction, and social role, as characterized by items like, "Am not sure where my life is going," "Feel that others misunderstand me," and "Act or feel in a way that does not fit me" (DeYoung, 2010b; 2014). No wonder that people with such psychological instability feel compelled to protect themselves by monitoring and varying their public appearance! They have little stable sense of self to fall back on, when deciding how to act. This insight may form a promising basis for future research into protective self-monitoring.

In conclusion, we believe that no one interested in self-monitoring can afford to ignore the findings reported here. They open wide new vistas onto theory and research on the construct, while simultaneously allowing for the integration of self-monitoring within the mainstream of personality research, as the latter moves toward the development of broad explanatory theories (DeYoung, 2014). Further, for anyone interested in the metatraits and their manifestation in social behavior, our results provide the keys to a treasure-trove: The extensive and vibrant literature on self-monitoring can be mined to develop novel understandings and hypotheses of the role of Stability and Plasticity in the social lives of individuals.

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Figure

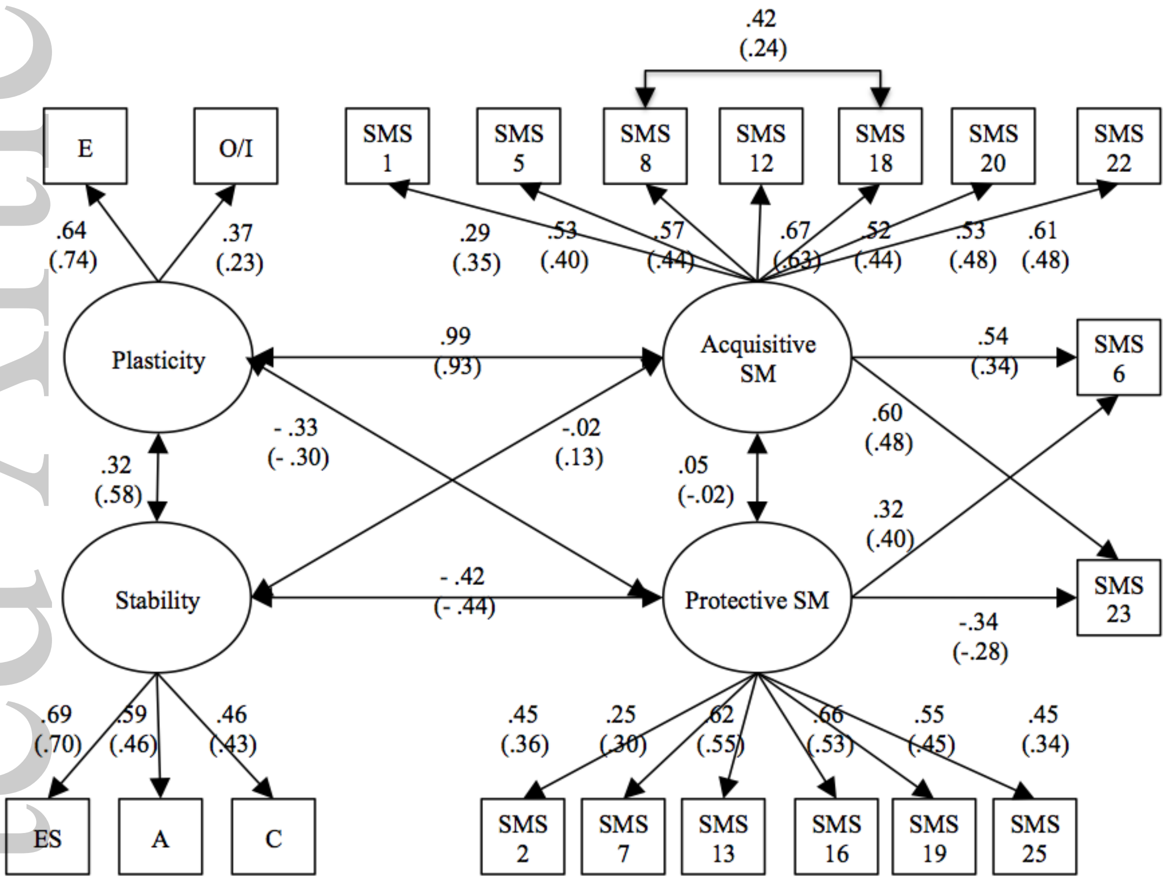

Figure 1. Relations between the metatraits and self-monitoring factors. Sample 1 (N = 522) and Sample 2 (N = 3,726), respectively; Sample 2 loadings in brackets. Standard errors omitted for readability, but are available on request from the corresponding author. All paths shown shown have 95% confidence intervals excluding zero except for Acquisitive SM and Protective SM (both Samples), and Acquisitive SM and Stability (Sample 1 only). See Table 3 for fit indices. E = Extraversion; O/I = Openness/Intellect; ES = Emotional Stability; A = Agreeableness; C = Conscientiousness; SMS = Self-Monitoring Scale; SMS items refer to the original order as presented in Snyder (1974).

Tables

Table 1

Unrotated Factor Loadings of Selected Self-Monitoring Scale Items

Item	Sample 1		Sample 2	
	Factor 1 (Acquisitive SM)	Factor 2 (Protective SM)	Factor 1 (Acquisitive SM)	Factor 2 (Protective SM)
SMS 1	**.318**	.082	**.392**	.113
SMS 2	-.018	**.448**	-.005	**.369**
SMS 5	**.527**	-.003	**.418**	.015
SMS 6	**.570**	.264	**.361**	**.346**
SMS 7	-.065	.296	-.033	**.328**
SMS 8	**.686**	.023	**.571**	.104
SMS 12	**.595**	-.103	**.537**	-.195
SMS 13	.143	**.602**	.102	**.530**
SMS 16	.119	**.636**	.028	**.520**
SMS 18	**.616**	.012	**.526**	.037
SMS 19	-.006	**.561**	-.006	**.456**
SMS 20	**.587**	-.127	**.549**	-.050
SMS 22	**.591**	-.111	**.412**	-.184
SMS 23	**.480**	**-.349**	**.390**	**-.312**
SMS 25	.087	**.460**	.064	**.346**

Note. N = 522 and 3,726, respectively, for Samples 1 and 2. Principal-axis factoring. Factor loadings ≥ .30 in absolute value are bolded.

Acquisitive and protective self-monitoring factors correspond to the empirically derived subscales of Briggs and Cheek (1988), which researchers labeled Public Performing and Other-Directedness, respectively.

Acquisitive self-monitoring indicators include SMS 1, 5, 8, 12, 18, 20, and 22; protective self-monitoring indicators include SMS 2, 7, 13, 16, 19, and 25); due to a history of cross-loading, items 6 and 23 were freed to load on both factors. Self-Monitoring Scale item numbers refer to the original order as presented in Snyder (1974).

Table 2

Correlations, Means, and Standard Deviations of Observed Variables for Samples 1 and 2

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1	SMS-R		.87	.32	.44	.18	.08	-.11	-.08	.49	.12	.47	.47	.08	.54	.49	.33	.25	.49	.14	.50	.40	.37	.30
2	Acquisitive SM	.90		.11	.51	.19	.11	-.09	-.04	.49	.02	.51	.48	.00	.61	.59	.12	.04	.58	.17	.59	.49	.47	.08
3	Protective SM	.36	.13		-.21	-.05	-.24	-.11	-.20	.10	.48	.02	.49	.47	.08	-.12	.61	.58	.04	.55	-.04	-.12	-.41	.50
4	Extraversion	.39	.47	-.26		.17	.34	.16	.14	.19	-.11	.24	.14	-.08	.24	.48	-.09	-.14	.26	-.08	.27	.36	.45	-.03
5	Openness/Intellect	.33	.36	-.01	.24		.05	.05	.04	.14	-.06	.18	.02	-.01	.15	.11	.00	-.01	.17	-.09	.16	.08	.03	-.04
6	Emotional Stability	.00	.02	-.20	.14	.09		.32	.29	.05	-.06	.10	-.07	-.06	.04	.13	-.14	-.16	.01	-.15	.09	.09	.23	-.09
7	Agreeableness	-.10	-.10	-.17	.09	.01	.43		.20	-.05	-.07	-.12	-.10	.04	-.09	-.06	-.11	-.15	-.05	.04	-.04	-.01	.04	-.05
8	Conscientiousness	-.10	-.06	-.26	.16	.03	.31	.22		-.01	-.09	-.01	-.13	-.05	-.06	.02	-.13	-.15	-.09	-.08	.00	.01	.13	-.06
9	SMS 1	.43	.44	.12	.08	.14	-.03	-.07	-.01		.04	.18	.15	.09	.26	.15	.07	.06	.20	.03	.25	.11	.13	.09
10	SMS 2	.15	.00	.51	-.17	-.08	-.10	-.18	-.14	.06		.02	.11	.08	.05	-.08	.18	.22	-.02	.20	-.03	-.06	-.09	.14
11	SMS 5	.56	.59	.05	.30	.27	.11	-.14	-.03	.16	.00		.15	-.03	.24	.22	.06	.03	.21	-.03	.23	.17	.15	.05
12	SMS 6	.59	.62	.41	.27	.23	-.07	-.13	-.15	.20	.07	.32		.12	.20	.19	.22	.17	.24	.22	.15	.11	.03	.15
13	SMS 7	.06	-.03	.45	-.15	-.04	.03	.06	-.05	.13	.07	-.04	.06		-.01	-.08	.18	.13	-.02	.17	-.03	-.08	-.12	.14
14	SMS 8	.60	.72	.09	.26	.26	.03	-.04	-.06	.21	-.05	.33	.38	.01		.21	.10	.08	.39	.01	.40	.12	.15	.04
15	SMS 12	.58	.64	-.04	.48	.26	.04	-.03	.00	.15	-.04	.32	.37	-.13	.33		-.02	-.09	.25	-.06	.25	.37	.34	-.02
16	SMS 13	.34	.13	.67	-.08	.06	-.18	-.18	-.17	.05	.27	.09	.23	.14	.15	.02		.33	.06	.24	.03	-.02	-.12	.16
17	SMS 16	.33	.11	.68	-.14	.08	-.15	-.15	-.19	.02	.30	.11	.26	.12	.07	.01	.49		.02	.19	-.03	-.06	-.16	.19
18	SMS 18	.56	.67	.07	.28	.26	-.03	-.06	-.06	.19	-.07	.29	.40	-.03	.59	.27	.08	.04		-.01	.27	.17	.14	.02
19	SMS 19	.17	.11	.63	-.19	-.10	-.18	-.03	-.21	.04	.30	-.10	.17	.22	.01	-.01	.28	.32	.03		-.04	-.06	-.11	.18
20	SMS 20	.54	.64	-.07	.25	.24	.10	-.03	.05	.23	-.08	.32	.19	-.12	.49	.35	.01	.00	.37	-.07		.21	.20	.00
21	SMS 22	.55	.64	-.05	.36	.21	.00	-.09	-.04	.19	.01	.28	.33	-.11	.34	.44	.01	.00	.31	-.03	.34		.28	-.03
22	SMS 23	.45	.52	-.40	.56	.19	.11	.06	.12	.16	-.11	.30	.16	-.13	.24	.40	-.14	-.15	.22	-.23	.29	.41		-.05
23	SMS 25	.33	.11	.58	-.10	-.01	-.11	-.09	-.10	.17	.23	.09	.12	.18	.01	.03	.26	.28	.05	.29	.02	-.01	-.12	
	M Sample 1	2.68	2.52	2.44	3.48	3.71	3.42	4.08	4.14	2.70	1.87	2.20	2.11	3.26	2.53	2.59	2.50	2.50	1.99	2.03	3.01	2.65	3.35	2.64
	SD Sample 1	0.57	0.72	0.64	0.66	0.57	0.64	0.49	0.48	1.20	0.94	1.37	1.20	1.21	1.40	1.21	1.30	1.28	1.35	1.06	1.36	1.20	1.21	1.23
	M Sample 2	0.53	0.51	0.50	2.90	3.44	2.70	3.01	2.92	0.61	0.25	0.47	0.43	0.68	0.55	0.41	0.56	0.72	0.47	0.25	0.62	0.34	0.48	0.58
	SD Sample 2	0.20	0.27	0.24	0.64	0.45	0.63	0.53	0.55	0.49	0.43	0.50	0.50	0.47	0.50	0.49	0.50	0.45	0.50	0.43	0.48	0.47	0.50	0.49

Note. Correlations for Sample 1 (N = 522) are presented below the diagonal; values greater than .09 in absolute value have 95% confidence intervals excluding zero. Correlations for Sample 2 (N = 3,726) are presented above the diagonal; values greater than .04 in absolute value have 95% confidence intervals excluding zero. SMS-R = 18-item Self-Monitoring Scale-Revised (Snyder & Gangestad, 1986); Acquisitive SM = acquisitive self-monitoring factor subscale (SMS 1, 5, 6, 8, 12, 18, 20, 22, and 23); Protective SM = protective self-monitoring factor subscale (SMS 2, 6, 7, 13, 16, 19, 23 (reverse-scored), and 25). Items 6 and 23 cross-loaded on both acquisitive and protective self-monitoring factors, and are included in both subscales; thus, their subscale correlation lacks experimental independence. Big Five values correspond to mean of self-ratings and average informant-ratings. Self-Monitoring Scale item numbers refer to the original order as presented in Snyder (1974).

Table 3

Fit of the Models Interrelating Self-Monitoring Factors and the Metatraits

	χ^2	*df*	TLI	CFI	SRMR	RMSEA	90% CI
Sample 1 (*N* = 552)							
Model 1: Unconstrained	466.48	161	.849	.872	.058	.059	.053, .065
Model 2: Constrained	466.49	162	.851	.873	.058	.058	.052, .065
Sample 2 (*N* = 3,726)							
Model 1: Unconstrained	1776.48	161	.819	.847	.049	.052	.050, .054
Model 2: Constrained	1779.28	162	.820	.847	.049	.052	.050, .054

Note. TLI = Tucker–Lewis index; CFI = comparative fit index; SRMR = standardized root-mean-squared residual; RMSEA = root-mean-square error of approximation; 90% CI = 90% confidence interval associated with RMSEA. Constrained model = covariance between Plasticity and acquisitive self-monitoring constrained to be 1.00.