This paper is currently under review

Why do items correlate with one another?

A conceptual analysis with relevance for general factors and network models

Daniel Leising¹², Julian Burger³, Johannes Zimmermann⁴, Martin Bäckström⁵,
Joshua Oltmanns⁶ & Brian Connelly⁷

¹Technische Universität Dresden, Germany

²McGill University, Montreal, Canada

³Universiteit Amsterdam, The Netherlands

⁴Universität Kassel, Germany

⁵Lunds Universitet, Sweden

⁶University of Kentucky, KT, USA

⁷University of Toronto, Canada

Address for Correspondence

Prof. Daniel Leising
Assessment and Intervention Research Unit
Technische Universität Dresden
01062 Dresden, Germany
Phone: +49 176 616 93286
Daniel.Leising@tu-dresden.de

Abstract

Most psychometric research relies heavily on patterns of correlations between items on which perceivers describe targets. Apart from the targets' actual ("substantive") characteristics, this type of data has been shown to also reflect a number of other, non-substantive sources of variation. This is problematic because each of these (semantic redundancy, attitudes, formal response styles) may all by itself account for correlations among items, which may then be *misinterpreted* in terms of substantive effects. We present an integrative theoretical account of how these non-substantive influences may affect the pattern of relationships between items. We also point out how this is relevant to the validity of conclusions drawn in research on "general factors" (of personality, psychopathology, and personality pathology) and on "network models". Furthermore, we discuss various ways of dealing with the problem, which is necessary before any correlations between items may be interpreted in terms of substantive associations between the targets' actual characteristics.

Keywords: Person perception, semantics, attitude, response style, psychometrics, measurement, network model, factor analysis

Introduction

Correlations between person-descriptive items constitute the backbone of psychometrics. Scale scores are computed because items correlate with one another, and are thus assumed to measure the same thing, or closely related things. Correlations between scales basically reflect the extent to which the items of each of those scales correlate with those of the respective other scale, on average. Several descriptive taxonomies of broad “personality traits” (e.g., the so-called “Big Five”) rest on the outcomes of factor analyses, which in turn are based on correlations between items. More recently, “network models” addressing the dynamic interplay of whole sets of person-descriptive variables have gained considerable traction. Again, these models are basically rooted in how strongly different items correlate with one another.

In the present paper, we present a systematic account of *why* items may correlate with one another. This is necessary because there is considerable confusion in the literature as to how item correlation patterns should be interpreted. The core problem that we address is the risk of mistaking associations between person *judgments* as direct reflections of associations between the *actual target characteristics* underlying those judgments. Judgments may, however, reflect several other influences apart from those actual target characteristics, and those influences may partly or even completely explain why items correlate with one another. In order to be able to make *valid* inferences regarding the meaning of inter-item correlations, researchers need to be aware of those other influences, and account for them in the way they conduct their research. Only after accomplishing that may they draw inferences regarding associations between actual target characteristics.

We present a conceptual analysis of five different mechanisms that may account for correlations between items. All of the components of this analysis have been discussed in the literature before (e.g., Brunswik 1956; Kenny, 1994, 2004; Leising, Scherbaum, Locke &

Zimmermann, 2015; Podsakoff, MacKenzie, Lee & Podsakoff, 2003; West & Kenny, 2011). The unique contribution of the present paper is that we integrate them all within a single, unified framework, and in a relatively formalized manner. We use this analysis to highlight crucial interpretational pitfalls in the analysis of person judgment data, and we provide concrete suggestions as to how these pitfalls may be avoided. In the next section, we present the five mechanisms, and address the ways in which their operation may be made visible. In the section after that, we discuss how these mechanisms are relevant to psychometrics, especially research on the so-called “general factors” (of personality, personality pathology and psychopathology) and on network models. We also ask how appropriately these fields have so far accounted for the various mechanisms that may be responsible for correlations between items, and close with a few concrete recommendations for future research in this regard.

Although we adopt a particular focus on the content domains of personality, personality disorders, and psychopathology, we note that the mechanisms outlined herein are similarly applicable to any domain in which judgment ratings are collected, such as supervisor ratings of job performance (e.g., Viswesvaran, Schmidt, & Ones, 2005), teacher ratings of children’s behavioral disinhibition (e.g., Bishop, Spence, & McDonald, 2003), or in appraising one’s subjective well-being (e.g., Eid & Diener, 2004).

The Basic Conceptual Model

Our primary concern in this this paper are the correlations that may exist between judgments on two different items. We will address the most common situation in which each target is judged by a different perceiver, and these dyads of targets and perceivers are the same across all items. All other possibilities will be ignored, for the sake of simplicity. Also, the model applies to other-ratings as well as self-ratings. In the latter case, the perceiver and the target in each dyad simply happen to be the same person. However, for illustrative purposes we will stick

with the more general case of other-ratings. For example, imagine that researchers were aiming to understand why *judgments* on two different items (“jovial” and “jealous”) correlate with one another. They recruit a sample of *targets* (e.g., Tina, Tom and Ted), each of whom is rated on these two items by a different perceiver (e.g., Peter, Paula, and Priscilla). It is straightforward to calculate the correlation (r_{jj}) between these judgements, but actually understanding the origins of that correlation is a thornier matter.

Figure 0 presents the conceptual model that we will use to analyze this issue in depth. The model integrates ideas from several previous models, such as Brunswik’s (1956) lens model, Kenny’s (1994, 2004) Weighted Average / PERSON model, and West & Kenny’s (2011) Truth and Bias model. It distinguishes between four different kinds of variables: Judgments (J), substance (S), attitudes (A), and response styles (R).

The *judgments* of the targets (t) that the perceivers (p) provide on the items (J1, J2) are our primary “dependent variables”. We are trying to understand the different factors that may contribute to such judgments. The judgments may vary depending on who judges whom, which is why they have a double “pt” index. In our model, judgments are color-coded *green*. Very often, judgments on individual items are later aggregated (e.g., summed) into what we will call “higher order judgments” (HOJ). These are also displayed in Figure 0. One example would be a scale score that is computed for each target, from the individual items (J1, J2) of a questionnaire. Another example would be a diagnosis that is assigned to some patients after checking the presence of a set of individual symptoms (J1 J2). A primary criterion for such aggregations is the extent to which items correlate with one another (r_{JJ}).

Figure 0. Full conceptual model. p = perceiver; t = target; (pt) = perceiver-target-dyad; S1, S2 = Two different substance variables (each contains actual differences between targets); J1, J2 = Judgments of the targets on two different items; r_{JJ} = Correlation between the two items; HOJ: Higher-order judgment (e.g., a scale score) that is derived from the individual items. A = Attitude; R = Formal Response Style; C = Substantive Cause.

Substance variables are color-coded blue in Figure 0. They contain factual information about differences between the targets that objectively exist, irrespective of the extent to which perceivers account for these differences in making their judgments. For example, Tina may smile (S1) seventeen times a day, on average, or Tom may say something negative about others (S2) only once a month. However, such differences may not only concern the targets' typical way of thinking, feeling, and behaving (a.k.a. "personality"), but also their specific life-circumstances (e.g., married) and the consequences that the targets bring about by interacting with their environment in ways typical for them (e.g., getting fired more often than others). In Figure 0, the fact that some actual target characteristics (e.g., behavior) may influence other actual target characteristics (e.g., consequences) is symbolized by the arrow pointing from S1 to

S2. For simplicity, we will ignore the fact that perceivers may differ from one another in terms of the actual characteristics of the same targets they were exposed to (information overlap; Kenny, 1994, 2004). Instead we will concentrate on the substance variation to which all perceivers have equal access.

In keeping with Brunswik's (1956) lens model, Figure 1 contains two different kinds of substance variables, which may be called "proximal" (S1 and S2) and "distal" (C). The distal C variable (standing for "cause") is thought to causally account for any co-variation between the more proximal substance variables. For example, a virus infection (C) may account for symptoms such as fever (S1) and headaches (S2) (note that "fever", "headaches" are *names* (J) that people use to denote certain phenomena, but the substance variables (S) are the *things that are denoted* by these names, and that exist regardless of how they are named). People who are infected with the virus – as compared to people who are not infected – tend to have higher temperatures (= fever) and to report more headaches. If the C variance is controlled for, the existing correlations among the symptoms will vanish (see the concept of "local stochastic independence"). Basically, any substance variable that varies between targets may assume the role of such a cause, be it certain childhood experiences, or a trauma, or a genetic disposition. The observable co-variation among the proximal substance variables may also be accounted for by more than one cause variable, but this will largely be ignored here for the sake of simplicity. It should be noted that the existence of a causal variable is *not* a requirement for judgments to take place. Judgments may just as well be purely "summatory" or "formative" in nature (Schmittmann et al., 2013), as we will explain further below.

Judgments (J) may also reflect the *attitudes* (A) that the perceivers have toward their targets (Leising, Scherbaum, Locke & Zimmermann, 2015; Peabody, 1967; Saucier, 1994). Attitudes capture the extent to which the perceivers like the targets (again, irrespective if they

ever report this). There are many possible influences on perceiver attitudes (color-coded red in Figure 1). For example, perceivers may differ from one another in how much they like the average person (A_p). Likewise, some perceivers may consistently favor certain targets over other targets ($A_{(pt)}$). Finally, some targets may be favored more than other targets by the average perceiver (A_t). All of these differences might contribute to the perceivers' overall attitudes toward their targets, and they may affect the perceivers' judgments of the targets on any item, to the extent that that item is evaluative (Edwards, 1953, 1957). Notably, "self-esteem" may be regarded a special case of attitude.

Finally, judgments (J) may also reflect so-called "formal response styles" (R), for which we use an orange color-code. Formal response styles concern individual perceivers' tendencies to respond to items in certain ways, irrespective of the specific evaluative or substantive content of those items (which is why we call them "formal"), and also irrespective of who is being judged. For example, some perceivers may prefer lower scores (e.g., 1) over higher scores (e.g., 7), whereas other perceivers may do the opposite. There are actually many different formal response styles that are conceptually independent of one another. For the sake of simplicity, however, Figure 1 contains only one rather than several different response style variables. As formal response styles are assumed to vary only between perceivers, this variable only has a single index (p).

Mechanisms Accounting for Correlations between Items

We will now use the conceptual framework introduced above to highlight five different mechanisms that may bring about a correlation between items. Understanding these mechanisms is of crucial and direct importance in regard to how such correlations (and, by extension, scale scores, factors, and whole networks of relationships between items or scales) should be interpreted. The first two mechanisms are about substance. These are the things that

most psychology researchers are primarily interested in. Investigating them with judgment data, however, is difficult, because this type of data also reflects the influences of at least three other mechanisms that may also account for correlations between items. These latter three have sometimes been comprehensively called “method factors” in the literature (Campbell & Fiske, 1959; Podsakoff et al., 2003).

The order in which the five mechanisms are presented largely follows our theoretical understanding of how person judgments come about. We display each mechanism in graphical form (in Figures 1 to 5), temporarily “knocking out” all the other mechanisms that may also account for a correlation between items to zero. That correlation, which is the focus of attention here, will be called r_{jj} . For each of the five mechanisms, we explain the associated meaning of a scale / factor score that would be computed from the items, the meaning of the correlation between the items, and the meaning of the correlation between an individual item and the scale / factor score. We also address possible ways of empirically disentangling the workings of each mechanism from those of the other mechanisms.

Mechanism 1: Common Substantive Causation

One reason for different items to correlate with one another is the existence of a common substantive cause that affects the substance variables which are reflected by these items. Figure 1 displays this situation. Here, each item (J1 and J2) reflects a different substance variable (S1 and S2), and the only reason that makes the items correlate with one another is the fact that these two substance variables are affected by the same substantive cause (C).

Figure 1. Mechanism 1: A correlation between two items is solely accounted for by common substantive causation. p = perceiver; t = target; S1, S2 = Two different substance variables (each contains actual differences between targets); J1, J2 = Judgments of the targets on two different items; r_{JJ} = Correlation between the two items; C = Substantive cause.

For example, a brain trauma (C) may simultaneously account for the occurrence of two different kinds of symptoms (S1, S2), which would make items describing those symptoms (J1: “headache”, J2: “dizziness”) correlate with one another. When looking only at targets with the trauma, or targets without the trauma, or when statistically controlling for the influence of the trauma, the correlation between the symptoms (and therefore, the items) should disappear (“local stochastic independence”). Of course, more than one causal factor may be at play, but that possibility will be ignored here, for the sake of simplicity. Also, the common substantive cause variable does not have to be *known* or *measurable* (yet) to exist and exert its effect. In fact, it is often the observed co-occurrence of symptoms (e.g., of an infectious disease) that comes first, and that then leads researchers to investigate the common substantive cause for that co-occurrence. Furthermore, common substantive causes (e.g., having a virus) may have yet more distal causes (e.g., having been exposed to people who carry the virus), and

sometimes common substantive causes turn out to be whole bundles of interconnected variables which would better be described as a dynamic interplay (see Mechanism 2).

When a correlation between items is *exclusively* accounted for by Mechanism 1, that correlation reflects the average strength of the effect of the common substantive cause on the proximal substance variables involved, the scale score reflects the targets' standings on the common cause variable, and the item-total correlations reflect the respective extents to which the proximal substance variables that are associated with each item are affected by the common cause. All of these associations are attenuated by the extent to which the individual items reflect "their" respective substance variables.

Mechanism 2: Dynamic Interplay of Substance Variables

Even in the absence of a common cause, substance variables may be correlated with one another because one variable affects another a causal fashion. For example, a target's disposition to get into fights more easily than other targets ($S1_t$) may cause that target to lose his or her job more often than other targets ($S2_t$). Such a pattern is displayed in Figure 2. Whole patterns of how variables affect other variables may be analyzed under a "network" or "dynamic systems" perspective" (Borsboom & Cramer, 2013; Epskamp, Borsboom & Fried, 2018; Schmittmann et al., 2013), and similar arguments have been put forth as a "functionalist" or "dynamic" account of personality (e.g., Cramer et al., 2012; Wood, Gardner, & Harms, 2015) and intelligence (van der Maas et al., 2006).

Figure 2. Mechanism 2: A correlation between two items is solely accounted for by a dynamic interplay of substance variables. p = perceiver; t = target; S1, S2 = Two different substance variables (each contains actual differences between targets); J1, J2 = Judgments of the targets on two different items; r_{JJ} = Correlation between the two items.

When a correlation between two items is *exclusively* accounted for by this mechanism, that correlation is a measure of how strongly the substance variables associated with the items influence each other, on average, the scale score is again a measure of the individual targets' average standings on the interacting substance variables, and the item-total correlation is a measure of the centrality of the substance variable that is associated with the item, in the network of all substance variables. All of these relationships are again attenuated by the extent to which the individual items reflect "their" respective substance variables. Of course, in reality the ways in which different substance variables are associated with one another will often be much more complicated than the ones used in our examples (e.g., there may be interactions, bidirectional effects or feedback loops).

Mechanism 3: Shared Semantic References

Another simple reason why items may correlate with one another is their reflecting the same “thing(s)”. An item may relate to any set of substance variables in any way. For example, people may be inclined to call an object a “house” (J1) if it has walls (S1) and a roof (S2). But people may also be inclined to call an object a “building” (J2) for some of the same reasons. The more the semantic references of two items overlap, the higher their correlation will be when applied to the same set of objects. The same is true for the universe of person-descriptive terms, pairs of which differ from one another in how much they are synonyms, antonyms, or unrelated. For example, the terms “sensitive” and “thin-skinned” obviously have similar semantic references, but dissimilar ones when each is compared with terms such as “easy-going” or “robust”, and the correlation pattern between four items is likely to look accordingly.

This issue is highlighted in Figure 3. To keep things simple, the Figure only contains a single instance of semantic redundancy: Both J1 and J2 are (partly fuelled by S1). This fact alone would suffice to make the two items correlate with one another. Notably, however, the “thing” that two items equally reflect may also be multidimensional. For example, judgments of how “nice” (J1) or “kind” (J2) targets are may both reflect the frequency with which the targets smile (S1) and the average number of promises the targets keep (S2), even if these two substance variables are *not* associated with one another. To capture this constellation, we would have to add another arrow pointing from S2 to J1 in Figure 3. In such a case, the “construct” that is represented by each item would be purely “formative” in nature (Schmittmann et al., 2013). If the two substance variables were also affected by a common substantive cause (Mechanism 1), that would add even more to the correlation between the items (as long as the semantic overlap is not already perfect). The construct represented by each item would then be “reflective” in nature (Schmittmann et al., 2013).

Figure 3. Mechanism 3: A correlation between two items is solely accounted for by semantic redundancy. p = perceiver; t = target; S1, S2 = Two different substance variables (each contains actual differences between targets); J1, J2 = Judgments of the targets on two different items; r_{JJ} = Correlation between the two items.

When a correlation between two items is *exclusively* accounted for by this mechanism, the correlation is a measure of the average level of semantic redundancy between items, the scale score is a measure of the substantive thing(s) that the items refer to, on average, and the item-total correlation is a measure of how closely a given item tracks that shared semantic base.

A special case of semantic redundancy is when the substance that is reflected by one item is *part of* the substance included in another item. For example, one item (J1: punctual) may reflect a relatively narrow substantive base (S1: being on time for appointments), whereas another item (J2: conscientious) may also reflect that base, but other kinds of substance variation as well (e.g., S2: frequency of vacuuming apartment, S3: hours spent studying per week). This breadth of associations between judgments and substance has been called “bandwidth”, “category breadth” or “level of abstraction” (Hampson, John & Goldberg, 1986). When the substantive base for one item is included in the substantive base for another item,

the two items will correlate, but this correlation will be smaller the greater the difference in bandwidth between the two items is.

Probably the easiest way of assessing this possible reason for why items may be correlated is to have the items explicitly rated for semantic redundancy. This may be accomplished by presenting raters with item-pairs and asking them about “the extent to which these terms constitute interchangeable descriptors of the same things”. Recently, automatized methods of determining semantic redundancy have been developed, which are based on computational linguistics. Here, pairs of terms are assessed in how often they occur in similar contexts within large text corpuses (Arnulf, Larsen, Martinsen & Bong, 2014; Garcia, Rosenberg, Al Nima, Granjard, Cloninger & Sikström, 2020; Sikström & Garcia, 2019). The two approaches should yield similar results, and the question as to how much incremental information the latter approach is capable of providing as compared to the former is an open one. Research into this question has barely begun (References). Another issue to keep in mind is that these measures of semantic synonymity may overlap significantly with measures of attitudes (see Mechanism 4) (Sikström study).

Mechanism 4: Shared Attitude Effects

Correlations between items may also come about because perceivers differ in the attitudes they have toward targets, and most items do reflect those attitudes to a considerable extent (Anderson, 1968; Dumas, Johnson & Lynch, 2002; Leising, Scherbaum, Locke & Zimmermann, 2015). Figures 4a and 4b display two variants of this mechanism: In Figure 4a, attitudes are independent of the substantive target characteristics that the items reflect. In Figure 4b, attitudes *do* depend on those characteristics. In reality, these mechanisms may operate at the same time, but we keep them separate here, for didactic reasons.

Figure 4a. Mechanism 4a: A correlation between two items is solely accounted for by perceiver attitudes that are unrelated to the substance reflected by either item. p = perceiver; t = target; (pt) = perceiver-target dyad; $S1$, $S2$ = Two different substance variables (each contains actual differences between targets); $J1$, $J2$ = Judgments of the targets on two different items; r_{JJ} = Correlation between the two items; A = Attitude.

In Figure 4a, the correlation between the items is completely accounted for by attitude components that are unrelated to the substance which is measured by the items: A_p stands for evaluative perceiver effects (i.e., some perceivers judging the average target more positively than other perceivers) (Rau et al., in press; Srivastava, Guglielmo & Beer, 2010; Wood, Harms &

Vazire, 2010). A_t stands for evaluative target effects (i.e., some targets being judged more positively than other targets by the average perceiver – *irrespective* of the specific substance that is reflected by the items at hand). $A_{(pt)}$ stands for evaluative relationship- or interaction-effects (i.e., some perceivers judging their specific targets more positively than would be expected on grounds of perceiver- and target-effects). Each of these three components alone would suffice to bring about a correlation between two items, as long as the items both reflect perceiver attitudes. In fact, research has consistently shown that most person-descriptive terms in the natural language are strongly evaluative (Anderson, 1968; Dumas, Johnson & Lynch, 2002; Leising, Ostrovski & Borkenau, 2012), and the extent to which they are rated as being evaluative aligns almost perfectly with how strongly their use reflects the perceivers' attitudes toward the targets (Leising, Gallrein & Dufner, 2014; Leising, Ostrovski & Zimmermann, 2013).

In Figure 4b, the situation is fundamentally different: Here, the substance that is measured by one of the items is what accounts for attitude differences, and these attitude differences are the sole reason why the two items correlate. For example, even if there is no systematic variance in A_p , A_t and $A_{(pt)}$, the items “attractive” ($J1_{pt}$) and “intelligent” ($J2_{pt}$) may turn out to be correlated, not because the two kinds of substance variation that these items assess are correlated, but because (e.g.) the actual target characteristics ($S1_t$) that are reflected by the use of the term “attractive” ($J1_{pt}$) tend to consensually evoke positive perceiver attitudes that will then also be reflected by the perceivers' use of the term “intelligent” ($J2_{pt}$) in describing the same targets. Of course, it would also be possible, that both of the substance variables underlying judgments on the two items feed affect the perceivers' attitudes. To reflect this situation appropriately, we would have to draw another arrow from $S1$ to $J1$ in Figure 4b. All of the ways in which perceiver attitudes may account for a correlation between items (displayed in Figures 4a and 4b) constitute instances of what is called a *halo effect* (Anusic, Schimmack,

Pinkus & Lockwood, 2009; Gräf & Unkelbach, 2016; Lance, LaPointe & Fiscaro, 1994; Nisbett & Wilson, 1977; Thorndike, 1920).

Figure 4b. Mechanism 4b: A correlation between two items is solely accounted for by perceiver attitudes that are based on the substance reflected by one of the two items. p = perceiver; t = target; (pt) = perceiver-target-dyad; S1, S2 = Two different substance variables (each contains actual differences between targets); J1, J2 = Judgments of the targets on two different items; r_{JJ} = Correlation between the two items; A = Attitude.

When a correlation between two items is *exclusively* accounted for by this mechanism, that correlation will be a measure of how much the perceivers' attitudes towards the targets (A_{pt}) vary, multiplied with how strongly the items reflect those attitude differences (Leising et al., 2015). The scale score will be a measure of those attitudes (and, to the extent to which the attitudes are based on the substance reflected by the items, that substance), and item-total correlations will be a measure of how evaluative the respective item is.

Accounting for Mechanism 4 in research is relatively straightforward. The perceivers' attitudes may easily be assessed by asking them how much they "like" their targets. In self-ratings, where the perceivers and the targets are the same persons, this basically amounts to asking those persons about their sense of self-esteem. Assuming honest responding, their responses may then be partialled out when computing associations between items. Correlations that remain after such partialling may be interpreted as not being rooted in perceiver attitudes. However, there remains a risk of "pouring out the baby with the bathwater" when the attitudes that are partialled out were strongly based on the targets' substantive characteristics (see below).

Furthermore, studies have shown that raters are capable of assessing the extent to which the endorsement of an item reflects positive or negative perceiver attitudes. Such ratings usually achieve close-to-perfect reliability with about 15 to 20 raters. They may be used to predict how strongly items should correlate with one another if those correlations were only driven by attitudes (Leising, Vogel, Waller & Zimmermann, under review), or they may be partialled out in profile analyses (Leising, Erbs & Fritz, 2010). Alternatively, one may attempt to create evaluatively neutral items that capture the same substantive content as the original items (Bäckström, Björklund & Larsson, 2009) and check how well results may be reproduced with these new items. The more this is the case, the less the correlations between items were accounted for by perceiver attitudes.

Mechanism 5: Formal Response Styles

Perceivers may differ from one another in which response options they prefer over other response options – irrespective of content. There may be preferences for high vs. low numerical scores, for specific locations on the response scale (left vs. middle vs. right), and/or for agreeing vs. disagreeing with statements in general. To the extent that the items permit

perceivers to act on those preferences, and to the extent that there is such variation between perceivers in the respective response styles, correlations between items may emerge (exception: if all targets are judged by the same perceiver). In most studies, however, the different response styles are at least partly confounded (e.g., when the affirmative response option is always located on the right-hand side), and we are not aware of any research systematically disentangling them. Figure 5 displays the hypothetical situation in which a correlation between items is brought about by a formal response style. Each of the above-named formal response styles would actually have to be displayed separately in the Figure, but we chose to only display one, for simplicity.

Figure 5. Mechanism 5: A correlation between two items is solely accounted for by the perceivers' formal response styles. p = perceiver; t = target; S1, S2 = Two different substance variables (each contains actual differences between targets); J1, J2 = Judgments of the targets on two different items; r_{JJ} = Correlation between the two items; R = Formal Response Style.

When a correlation between two items is exclusively accounted for by this mechanism, that correlation will be a measure of the response style variation between perceivers, attenuated by the extent to which both items reflect those response styles. The scale score will reflect the respective perceiver's location on the respective response style continuum, and the

item-total correlation will reflect the extent to which the respective item measures the response style.

On a side note, the formal response style called “extreme responding” (Wetzel, Lüdtke, Zettler & Böhnke, 2015; Wetzel, Carstensen & Böhnke, 2013) occupies a somewhat special role in this regard: It captures differences between perceivers in how much they tend to exhaust the whole range of the response continuum, as opposed to providing ratings that are similar to one another. This response style may *not* by itself account for any inter-item correlations, but it may increase or reduce any existing correlations, because it will affect the proportion of systematic (i.e., reliable) variance in one’s data.

The workings of Mechanism 5 may be accounted for in several ways in research. For example, it would be possible to systematically assess the perceivers’ formal response styles and then check how well the results of a study hold up when these sources of variation are controlled for. An ideal assessment of response styles requires that all perceivers rate the same, previously unknown target persons based on the same information (e.g., videotapes), in order to rule out the possibility that the judgments are affected by actual differences between targets. It also requires that the itemset is balanced in terms of content and evaluation, which is actually much more difficult to achieve than it sounds. At present, we are not aware of any successful attempt at doing so. We are also not aware of any successful attempt at disentangling the various formal response styles that may exist (e.g., acquiescence, preference for high numbers, preference for the left-hand side of the response scale) from one another. An alternative and relatively simple approach is to use a response format that makes it impossible for perceivers to express their formal response styles in their ratings (e.g., Block, 2008), and then compare the results with those that are obtained without such restrictions.

Relevance of the Five Mechanisms for Assessment and Research

Up to this point, we may have conveyed the impression that our conceptual analysis is mainly an academic exercise with little or no real-world implications. It is not. Quite to the contrary, this analysis is directly relevant to how patterns of associations between items and/or scales may or may not be appropriately interpreted. Before any conclusions regarding associations between substance variables (Mechanisms 1 and 2) may be drawn from judgment data, it is necessary to control for the possible confounding influence of semantic redundancy, shared attitudes, and formal response styles (Mechanisms 3, 4 and 5). We will now briefly address the general relevance of the latter three mechanisms with regard to scale score computation, before we talk about their relevance for general factor and network model research more specifically.

Scale Score Computation

So far, we only addressed the question of how correlations between individual items may come about. However, most research in personality and social psychology bases its analyses on *scales* comprising many items, rather than individual items. The reason is that, by aggregating across items, one may expect reliability to increase, because unsystematic error is likely to cancel out more across a greater number of “parallel” assessments. However, the resulting aggregate score will not necessarily reflect more *substantive* variation. This will only be the case if (a) the items of the scale actually do refer to the same, or related substance variables, and (b) measures are taken against a possible accumulation of the influences of Mechanisms 4 and 5. Unless such measures are taken, a scale score may just as well become a reliable measure of perceiver attitudes and/or formal response styles. This should become evident by looking at Figure 0 again: A scale score would be an example of the higher-order judgment (HOJ) in this figure, which is fuelled by judgments on individual items (J1 and J2). Even

if the items have nothing at all in common in terms of substance, a scale score may still achieve a high level of internal consistency, and correlate with any other variable that contains some of the same attitude or response style variance (Leising, Vogel, Waller & Zimmermann, under review). For example, when a self-report scale comprises numerous items asking participants whether they are “good” (or “bad”) at something, and the actual substantive skills that the individual items refer to are diverse and uncorrelated, the overall scale score will basically be just a highly reliable measure of the participants’ self-esteem, with little or no substantive basis anymore. Furthermore, such a scale may be expected to correlate with any other self-report scale that also reflects the participants’ self-esteem (which applies to almost any scale). Thus, computing scale scores by aggregating across items may sometimes *exacerbate* rather than mitigate the problem of how to appropriately interpret correlation patterns.

Relevance for “General Factor” Research

Three largely independent literatures have emerged regarding general factors of (a) personality, (b) general psychopathology, and (c) personality pathology (Caspi & Moffitt, 2018; Davies, Connelly, Ones, & Birkland, 2015; Irwing, 2013; Sharp et al., 2015). Each of these relatively unique literatures grapples with the meaning of one common superordinate factor extracted from a group of indicators with oftentimes different substantive meanings. Several interpretations of this superordinate factor have been put forward by researchers in each area (e.g., Caspi & Moffitt, 2018; Oltmanns, Smith, Oltmanns, & Widiger, 2018; Revelle & Wilt, 2013; Sharp et al., 2015; van der Linden, te Nijenhuis, J., & Bakker, 2010), but there has been little integration across the three domains (exception: Oltmanns et al., 2018). In addition, the various mechanisms that may bring about a general factor in a dataset (see above) are not systematically accounted for in most of the respective studies. Understanding these mechanisms, however, including the ways in which their operation depends on the specific

properties of a study's research design and data, is a necessary prerequisite for being able to properly interpret the *nature* of the general factor.

To illustrate this point, Figures 6 and 7 contain examples of two of the most often used factor models in this type of research. Figure 6 displays a bifactor model, whereas Figure 7 displayed a higher-order factor model. The main difference between them is that in the former model the general factor has a direct relationship with each individual item, whereas in the latter model the general factor is only indirectly related to the items, via the first-order scale scores. In each figure, the variables displayed on the right-hand side reflect the various mechanisms that may contribute to the formation of person judgments (and thus to correlations between items), according to our model (see above). The variables displayed on the left-hand side are three factors (two specific and one general) that may be introduced to explain the existing co-variation among the items or scales. The figures are simplified in several ways, for didactic reasons. For example, the individual attitude components (A_p , $A_{(pt)}$, A_t) are not separately displayed, and the two specific substance variables (S2 and S3) would more appropriately be displayed as four specific substance variables (S2 to S5; each being associated with exactly one item), of which the first two (S2 and S3, fuelling) may also reflect a common substantive cause (S6), and the latter two (S4 and S5) may reflect another common substantive cause (S7). All of this is ignored here, for simplicity. The main takeaway from the Figures 6 and 7 is that, regardless of the factoring technique that is applied to a dataset, the general factor may capture any mixture of shared substantive (S1), attitude (A) and/or response style variance (R).

Figure 6. The model applied to bifactor factoring. p = perceiver; t = target; S1, S2, S3 = Three different substance variables (each contains actual differences between targets); J1, J2, J3, J4 = Judgments of the targets on four different items; A = Attitude; R = Formal Response Style; F1, F2 = Two factors explain the co-variation among specific subsets of items; GF = General factor explaining the covariation among all items.

Figure 7. The model applied to higher-order factoring. p = perceiver; t = target; S1, S2, S3 = Three different substance variables (each contains actual differences between targets); J1, J2, J3, J4 = Judgments of the targets on four different items; A = Attitude; R = Formal Response Style; F1, F2 = Two factors explaining the co-variation among specific subsets of items; GF = General factor explaining the co-variation among F1 and F2.

Research on General Factors in person judgment originally evolved from higher-order research on the factorial structure of psychopathology (Achenbach, 1966) and personality (Digman, 1997). In terms of conceptual approach, it aligns quite closely with research on “g,” the general factor of intelligence (Spearman, 1904). The starting point for that research was Spearman’s observation of a “positive manifold” in intelligence testing data: Persons who were better at solving certain kinds of tasks tended to be better at solving other kinds of tasks, as well. Spearman thus proposed the existence of a common cause (g) accounting for that

manifold. In terms of our conceptual analysis, this may be seen as an example of the *supposed* operation of Mechanism 1. Since then, intelligence research has evolved considerably, and shown that models comprising several unrelated cause factors or hierarchical factors tend to fit the data better than a single common factor. More recently, dynamic substantive interplay explanations (Mechanism 2) for why intellectual capacities tend correlate with one another have been advanced as well (van der Maas, 2006).

However, the present paper is not about intelligence, but about person judgment, which begs the following, crucial distinction: While intelligence researchers have the luxury of being able to deal with relatively objective data (i.e., test results), researchers interested in social judgments also have to consider the various additional influences that may shape such judgments *apart* from the mere substance. We will now briefly review some of major contributions to the literature in this field, focusing specifically on whether and how these intervening processes were accounted for, and what the respective outcome was.

Musek (2007) extracted a general factor of personality (GFP) from self-reported indicators of the five-factor model (FFM) of personality. Across three samples using three separate measures of the FFM, the GFP model had good fit indices and the GFP explained a significant amount of variance. Moreover, the GFP correlated with life satisfaction, self-esteem, and positive affect, and negatively with negative affect. Musek wrote that the GFP represents “positive versus negative aspects of personality” (p. 1228). Similar factors have been extracted from self-reports using multiple personality measures and models (Rushton & Irwing, 2011), with some of this research actually predating the coining of the term “general factor of personality” (Furr & Funder, 1998; Bono & Judge, 2003). They are usually found to be associated with important, self-reported life outcomes such as job performance and subjective well-being (Burns et al., 2017; Pelt, van der Linden, Dunkel, & Born, 2017; van der Linden, te Nijenhuis, &

Bakker, 2010). Some researchers actually interpret the GFP in line with our Mechanism 1, that is, as a higher-order substance factor (C_t).

There is, however, a sizeable literature calling such substantive interpretations of the GFP into question, for various reasons: First, research has shown that perceiver attitudes (A_{pt}) *are* reflected in most person judgments and, accordingly, in the factors that may be extracted from such judgments. For example, Anusic et al. (2009) demonstrated the existence of an evaluative “halo” factor reflecting the overall positivity of targets’ self-judgments, independent of the substance that is shared between judgments of the targets by the targets themselves and by informants. They also showed that this factor closely aligns with the targets self-esteem, which is basically the targets’ attitude toward themselves.

Second, when the GFP is modelled using multi-source rather than single-source data, it tends to disappear, or at least to be substantially weakened (e.g. Chang, Connelly & Geeza, 2012; Danay & Ziegler, 2011; Revelle & Wilt, 2013; Riemann & Kandler, 2010). For example, for the research by Chang et al. (2012), 45 independent samples from 44 studies using self- and informant-ratings of the same target persons were collected and jointly analyzed according to the standards of multi-trait multi-method analysis (MTMM; Campbell & Fiske, 1959). The focus lay on the extent to which correlations between different personality ratings would depend on whether those ratings are provided by the same persons, or by different persons (e.g., self vs. informant). Hetero-trait mono-method correlations within informant-ratings (= same data source) turned out to be substantially higher ($\underline{\rho} = .16$) than hetero-trait hetero-method correlations between self- and informant-ratings ($\underline{\rho} = .03$), and between different informants ($\underline{\rho} = .04$) (= different data sources). This means that most – but not all – of the variance that was apparently shared between ratings (of different traits) was only shared as long as the ratings

came from the same persons, strongly suggesting the operation of rater-specific biases (such as non-shared attitudes and formal response styles).

Third, when the GFP is modelled with items that have been “neutralized” in terms of evaluative content, the GFP is also greatly reduced in saturation (Bäckström, Björklund & Larsson, 2009). For example, Bäckström and Björklund (2016) were able to show that the general factor of personality could be significantly weakened by rephrasing items in a more neutral/less evaluative fashion (from $\omega_H = .53$ to $\omega_H = .27$). Given that the evaluativeness of items basically equals the extent to which these items reflect the perceivers’ attitude toward the targets (Leising et al., 2013, 2014, 2015), this finding also supports the view that much of the GFP variance may be attitude variance. When items are framed in a less evaluative fashion, their criterion validity seems to remain largely unchanged (Bäckström, Björklund, and Larsson, 2014), which suggests that substance and attitudes may in fact be largely independent of one another (see Mechanism 4a). Furthermore, Bäckström and Björklund (2014, study 3) showed that people who were high on the GFP in self-ratings also tended to be high on the GFP when rating *others*. In other words, they tended to rate high on items with a positive evaluative tone, regardless of whom they rated. This suggests that evaluative perceiver-effects (A_p) specifically contribute to the GFP variance, as well.

Fourth, it has been shown that items loading in the *same* direction on the GFP often seem to have *opposite* semantic references: Pettersson, Turkheimer, Horn & Menatti (2014) had a sample of participants describe themselves using 30 sets of “quadruplets”, each comprising four items that were balanced in terms of valence and content (cf. Borkenau & Ostendorf, 1989; Peabody, 1967): For each quadruplet, items a and b were assumed to reflect high levels whereas items c and d were assumed to reflect low levels of the respective content dimension. In addition, whereas items a and c had a positive evaluative tone, items b and d had a negative

evaluative tone (e.g., a: “assertive”, b: “overbearing”, c: “modest”, d: “submissive”). Note that these specifics directly concern the signs of the associations symbolized by the arrows pointing from the S and A-variables to the J variable in Figures 0, 4a and 4b.

When factored, the general factor that emerged clearly assembled items with similar valence but opposite semantic references. Based on this finding, the authors concluded that “it is unlikely that a behavioural style could be characterized by so many paradoxical pairs of descriptors, so this dimension may be better interpreted as a response bias rather than as a description of a consistent behavioural propensity” (p. 299). By response bias, these authors clearly mean the perceivers’ attitudes. Taken together, all of these findings consistently suggest that a substantial proportion of GFP variance is attitudinal in nature.

More recently, two relatively independent literatures have emerged that highlight general factors of general psychopathology, and of personality disorder more specifically. So far, the interpretation of these factors has *not* been as controversial as that of the GFP, which may in part be due to a lack of conceptual analysis.

The general factor of psychopathology (“*p*-factor”) has been observed in numerous datasets, explaining significant amounts of variance, and correlating with criteria such as a family history of psychiatric disorder, childhood maltreatment, cognitive impairment, and motor skills (Caspi et al. 2014; Lahey et al., 2012). The highest loading variables on the *p*-factor are usually indicators of psychotic disorders (Caspi et al., 2014; Oltmanns et al., 2018). Substantive interpretations of the *p*-factor predominate, such as: thought dysfunction (Caspi & Moffitt, 2018), shared etiologies of psychopathology (Lahey et al., 2012), impulsive responsivity to emotion (Carver, Johnson, & Timpano, 2017), neuroticism (Tackett et al, 2013), and “secondary impairment” (Oltmanns et al., 2018).

In the original p-factor study by Caspi et al. (2014), 1000 participants from the Dunedin Multidisciplinary Health and Development Study underwent clinical interviews at ages 18, 21, 26, 32 and 38. A broad range of psychiatric symptoms was assessed. According to the authors, almost all of these symptoms (99%) were positively correlated with one another, suggesting a “positive manifold” akin to the one discovered by Spearman in his research on general intelligence (g). Confirmatory Factor Analyses controlling for interviewer-effects showed that a solution with three correlated factors (Internalizing, Externalizing, and Thought Disorder) fitted the symptom data best, but also that an overarching general factor (general psychopathology, p) always remained. In terms of content, this factor was almost perfectly aligned with the Thought Disorder factor, comprising symptoms of mania, schizophrenia, and OCD.

Given its longitudinal nature and the use of different interviewers for each target, the Caspi study affords some of the strongest evidence there is in favor of the substantive nature of a general factor of psychopathology (p). This general factor was also substantially correlated with some of the targets’ personality traits (Agreeableness: $r = -.31$, Neuroticism: $r = .42$, Conscientiousness: $r = -.31$), as reported by informants, which again points to the potential overlap between general factors from the personality and psychopathology domains (Oltmanns et al., 2018). In regard to this study, however, the following important point needs to be acknowledged: Data that is obtained using interviews is far from being objective, but strongly depends on what the interviewees are able and willing to say about themselves. This may be particularly relevant in assessments of psychopathology, because a large proportion of that measurement domain (e.g., depression, anxiety, somatization) is by definition anchored in what people say about themselves (e.g., how much they suffer, how strong the pain is, how much interest they have in things). Patients are seen as “having” these problems largely to the extent that they report having them. It is thus not unlikely that some or even most of the p-factor

variance in the Caspi et al. (2014) study is rooted in the targets' stable tendencies to attribute many or few *problems* to themselves, in relative independence of the specific nature of those problems. This would explain why (e.g.) symptoms of mania, schizophrenia and OCD were found to cluster together, even though these are usually considered quite distinct syndromes. Notably, given the fact that psychopathological symptoms are generally seen as highly undesirable, the attribution of such symptoms to people (e.g., oneself) may be particularly prone to reflecting the perceivers' attitude toward the targets. We are not aware of any study directly investigating this issue, however, and neither are we aware of any research into the possible contribution of semantic redundancy or formal response styles in the emergence of the p-factor.

The (smaller) literature on the general factor of personality disorder ("g-PD") also offers mainly substantive interpretations of the g-PD in particular: general interpersonal dysfunction (Jahng et al., 2011), borderline personality disorder, or self- and interpersonal functioning deficits (Sharp et al., 2015; Wright et al., 2016) as assessed by Criterion A ("level of personality functioning") of the Alternative PD model (AMPD) in DSM-5 (APA, 2013; Bender, Morey & Skodol, 2011). The highest-loading indicators on the g-PD have varied by study: Individual borderline personality disorder criteria (Sharp et al., 2015; Wright et al., 2016), paranoid / dependent scales (Jahng et al.), and avoidant / dependent / borderline scales (Oltmanns et al., 2018). A recent study by Leising, Scherbaum, Packmohr and Zimmermann (2018) found that the official "severity" grading of the level of personality functioning scale in DSM-5 (which basically assesses the g-PD) correlates almost perfectly with the social desirability of the individual person-descriptions associated with those levels. This strongly suggest an involvement of Mechanism 4. According to our knowledge, possible influences of semantic redundancy and/or formal response styles have never been investigated regarding the g-PD. In a first attempt at integrating these three separate literatures, Oltmanns et al. (2018) extracted the GFP, g-PD, and

p-factor from the same self-report dataset ($N = 474$) and found them to be very highly intercorrelated ($r_{g\text{-}PD/p} = .92$, $r_{g\text{-}PD/GFP} = .92$, and $r_{GFP/p} = -.70$). This suggests that the three constructs may largely be considered different names for the same thing, or closely related things, and that research findings pertaining to one of the three is also relevant to the other two. In another dataset ($N = 1,200$) using multi-method assessment, the GFP and g-PD were again found to be highly correlated $r = -.82$. Furthermore, the g-PD and GFP were found to be correlated with a broad composite impairment scale comprised of social support, insomnia, and physical health variables $r = .68$ and $r = -.65$, respectively.

There can be no doubt that General Factors do exist in judgments of personality, and in judgments of general and personality pathology. Ample empirical evidence using single-source data unequivocally supports this conclusion (Furr & Funder, 1998; Bono & Judge, 2003; Judge, Erez, Bono & Thoresen, 2002; Musek, 2007): Some perceivers *do* describe their targets in a more positive manner than other perceivers describe theirs. The far more interesting question pertains to the *nature* of these general factors. Research clearly suggest that perceiver attitudes do play an important role in this regard. However, we are not aware of any research that has looked specifically into possible contributions of semantic redundancy and/or formal response styles.

Relevance for Research Using Network Models

Another major strand of research literature to which our conceptual analysis directly applies is the literature on “network models” (including the so-called “dynamical systems”). Here, the core idea is that correlations between items are not necessarily attributable to “common substantive causes” (Mechanism 1), but to how the substance components that are reflected by the items causally affect each other (Mechanism 2). Over the past decade or so, this approach has gained considerable traction in both personality (Cramer et al., 2012; Wood,

Hensler Gardner & Harms, 2015) and clinical psychology (Borsboom & Cramer 2013; Robinaugh, Hoekstra, Toner, & Borsboom, 2020) psychology, as well as their intersection (Lunansky, van Borkulo, & Borsboom, 2019). However, most of the basic ideas within this approach are in fact decades old, and even well-ingrained in contemporary clinical practice. For example, Wessels et al. (2016) recently demonstrated how the classic clinical heuristics from cognitive behavioral therapy (e.g., Kanfer & Saslow, 1969; Kanfer & Schmelzer, 2005) may be transformed into a hierarchical structural equation model, and thus serve as a research tool. Figure 8 displays a version of this model.

Figure 8. Hierarchical structural equation model version the SORKC / ABC-model from cognitive behavioral therapy, as outlined by Wessels et al. (2016). Average person part (variation is over time): SE = External aspect of the current situation, SI = internal aspect of the current situation, IR = Internal Representation of the current situation, RE = External Response (directed toward the environment), RI = Internal Response (directed toward oneself), CE = External Consequence, CE = Internal Consequence. “Personality” part (variation is between targets): random effects (symbolized by thick white arrows) on (1) IR, (2) RE or RE, (3) link between SE or SI and IR, (4) link between IR and RE or RI.

In its original form, the model is used to explain why psychopathological symptoms such as anxiety tend to persevere, despite their having unwanted long-term consequences. However, Wessels et al. (2016) showed how the same basic conceptual model may just as well be applied to the personality domain. For our purposes here, it suffices to briefly recount the following points: (a) The model contains the internal (S_i ; e.g., recent caffeine intake) and the external (S_e ; e.g., speaking in front of an audience) aspects of the current situation which the *average* target person will internally represent (IR, e.g., as “threatening”) in certain ways. Such an internal representation may trigger internal (R_i ; e.g., soothing self-verbalizations) and/or external (R_e ; e.g., joking) responses from the average target, the difference between them being that the former primarily affect the target and the latter primarily affect the environment. These responses may then lead to internal (C_i ; e.g., distraction) or external (C_e ; e.g., audience laughing) consequences, which may in turn shape the situations that a person encounters in the future. At this level (average person), variation in the data is over time.

(b) “Personality” is the totality of all between-target random effects (represented by thick, numbered arrows in Figure 1) on IR (arrow 1; e.g., some targets interpret *all* situations as being more threatening than other targets) and R (arrow 2; e.g., some targets react to *all* situations with more joking than other targets), as well as on the links between S and IR (arrow 3; e.g., some targets perceive speaking in front of an audience as a *particularly* threatening situation) and the links between IR and R (arrow 4; e.g., some targets react *particularly* to situations they perceive as threatening with more joking).

(c) Due to the dynamic nature of the model, any such random effect may by itself suffice to bring about important consequences for the target and/or (people in the) target’s environment. Such “consequences of personality” have been the subject of many scientific investigations, and probably constitute one of the main reasons why personality research is

being conducted at all. By tying such consequences to imagined ideal-states (a.k.a. “values”), it becomes possible to determine how “problematic” a person’s specific ways of interacting with the environment are, especially in the long run. This is directly relevant in diagnosing personality pathology (Leising & Zimmermann, 2011).

The complex ways in which whole sets of substance variables affect each other are the focus of interest within the literature on network models and dynamical systems. Note that all of the nodes in Figure 8 are displayed in blue, because these models are supposed to reflect actual causal relationships between substance variables. However, the vast majority of the data that is subjected to statistical analyses in this research is *judgment* data. All four of the above-named types of between-target random effects may be assessed by a person descriptive item. For example: (1) “The person tends to interpret the average situation as more threatening than the average person does”; (2) “The person tends to make more jokes than the average person does”; (3) “The person tends to interpret situations in which other people are present as particularly threatening”; (4) “The person tends to react particularly to situations that s/he perceives as threatening by making jokes”. Moreover, items may capture any *consequences* that are brought about by such random effects (e.g., “This person tends to be liked by others”), as well as any *combination* of model components (e.g., “This person tends to be liked by others because s/he makes a lot of jokes”).

However, any correlation that is found between such judgments may not only reflect causal effects of substance variables on one another, but – because we are dealing with judgment data – shared semantics (Mechanism 3), and/or shared attitude effects (Mechanism 4), and/or formal response style effects (Mechanism 5). The latter mechanism may primarily affect the overall level of correlatedness between nodes in a network: On the one hand, it may account for an *underestimation* of relationships in networks based on data that is provided by

the same perceiver (e.g., intensive longitudinal data collection using the experience sampling method, ESM; Stone & Schiffman, 1994). On the other hand, it may account for an *overestimation* of relationships when each target is judged by a different perceiver, but these perceivers stay the same across items (which is the most typical case).

Mechanisms 3 and 4 may pose even greater trouble for the validity of conclusions drawn from network analyses, because these mechanisms directly affect the differential strengths of associations between individual items or scales, which are what network analysis is basically all about. The reason is that items differ from one another in terms of how strongly they reflect perceiver attitudes and/or in terms of semantic references. Accordingly, *pairs* of items differ from one another in how strongly *both* items reflect perceiver attitudes, and in how much they share semantic references. These differences alone would already suffice to create a differentiated pattern of item intercorrelations, which may easily be misinterpreted in terms of substantive causality.

Moreover, models used for estimating network models aim to take dependence structures into account, for instance through calculating partial-correlations between items (Epskamp & Fried, 2018; Epskamp, Borsboom, & Fried, 2018). As a result, the pairwise relations that are estimated between items often reflect to their relationship after controlling for all other items in the system. Due to this dependency, any relationship between items that arises from factors other than substance (such as Mechanisms 3 – 5) would threaten not only the validity of the estimated relationship between those items, but the validity of the estimated relationships between all other items, as well.

The field of network psychometrics borrows concepts from social network analysis (Borgatti, Mehra, Brass, & Labianca, 2009), such as analyzing which nodes are most “central” to a given network structure. A node’s *strength* (sometimes referred to as *degree* or *expected*

influence), for instance, is a measure of centrality that sums up all of the absolute incoming/outgoing edge weights for a given node in the network. Such measures have gained increasing popularity, especially in clinical psychology (Fried, Epskamp, Nesse, Tuerlinckx, & Borsboom, 2016). The reason is that more central nodes may be predestined to become a focus of therapeutic treatment, because by affecting them one may have the greatest impact on the dynamics of the (maladaptive) network as a whole. While some studies did find predictive effects of centrality estimates for treatment outcome (Elliott, Jones, & Schmidt, 2018), other literature calls for caution in using centrality estimates to identify targets of intervention (Bringmann et al., 2019).

One reason why such caution is warranted is, again, that patterns of correlations between items may reflect different degrees of pair-wise semantic redundancy (Mechanism 3; Fried & Cramer, 2017) and/or different degrees of joint evaluativeness (Mechanism 4). As a consequence, the estimated centrality of an item in a network of items may simply be a reflection of how much the semantic references of that item overlap with those of all other items in that network (with the most “central” item being the most redundant with the average other item), and/or of the extent to which that item reflects the same perceiver attitudes that all other items also reflect to some degree (with the most “central item” reflecting those attitudes most strongly).

There are statistical procedures that aim to discover conceptual redundancies in psychometric networks, for example the *goldbricker* algorithm (Jones, 2018). The logic behind such algorithms is that if two items are conceptually redundant, they should exhibit similar relationships with all other variables in a network. We are not aware of any research controlling for item evaluativeness in deriving psychometric networks.

Ways of Dealing with the Problem(s)

Most research in personality, social and clinical psychology aims to investigate the actual characteristics of target persons (e.g., how such characteristics are associated with one another, or how they respond to experimental manipulations). At the same time, however, most of the respective empirical investigations are based on *judgment* data, rather than objective data. It has long been recognized that so-called “method factors” may affect such data, apart from the substantive target characteristics that psychology researchers are most interested in (Campbell & Fiske, 1959; Podsakoff et al., 2003). This is particularly problematic when analyses are based on *correlations* between items or scales, because such correlations may be partly or even completely accounted for by shared semantic references, shared attitude effects, or the perceivers’ formal response styles. This clearly applies to most of psychometrics, including research into general factors, and network models. When using judgment data, *all* of these competing influences need to be appropriately accounted for, before any conclusions regarding associations between substance variables may be drawn. Only then will it be appropriate to speculate about (e.g.) the biological underpinnings of a general factor of personality or psychopathology, or to make a particular variable in a network of symptoms the focus of clinical attention due its functional centrality in that network.

Our brief, eclectic review of the literature showed that (a) some strong research into the general factor of personality *has* accounted for attitude effects, and shown them to be of very high relevance. However, research into general factors of psychopathology and personality pathology has largely ignored these influences so far. Furthermore, all three strands of general factor literature have largely ignored the problem of semantic redundancy, and the problem of formal response styles. Our review also showed that (b) there is an awareness of the semantic redundancy issue in the network models literature, including some suggestions as to how this

issue may be dealt with. At the same time, shared attitude effects and formal response styles are largely ignored as potential validity threats in this literature. In the remainder of this paper, we will briefly review four broad strategies that have been proposed for addressing these validity threats.

Strategy 1: Use objective data

The first and most intuitive strategy would be to measure substance variables objectively (i.e., unfiltered by human perception). This is what is done in intelligence research, and similarly objective assessments are possible in personality, clinical, and social psychology. For example, one might assess the loudness of the targets' voices, the number of words they speak per minute, the movements of their facial muscles, or the number of hours they spend watching TV or interacting with others (e.g., Vazire & Mehl, 2008). All of these would be examples of the many different ways in which the target persons tend to interact with their environment. One might also assess target-specific characteristics of that environment itself, such as the number of phone calls or text messages a target receives per day, or a target's monthly salary. These latter ones may be interpreted as "traces" or consequences of the targets' specific ways of interacting with their environment (Gosling, Ko, Mannarelli & Morris, 2002; Stachl et al., in press; Wessels, Zimmermann & Leising, 2016). When correlations emerge among such objective assessments, they may not be accounted for by semantic redundancy, perceiver attitudes, or formal response styles, because no human *raters* were involved in obtaining the data. However, collecting this type of data is often exceedingly difficult, sometimes fraught with ethical problems (e.g., regarding consent), and in many cases the relevant substance variables are not even yet known (Wiedenroth & Leising, in press). In fact, the substance that *matters* the most to us humans may often consist of highly complex *compounds* of individual variables that are only construed in the heads of perceivers - a process

closely related to what the term “semantics” refers to, and about which we know very little in person perception research (e.g., imagine modelling the substantive underpinnings of “jealousy” in terms of objectively measurable data). For these reasons, only few studies in personality research to date have applied this strategy, and the results have often been quite ambiguous in terms of what they *mean* psychologically. We are therefore confident that, for the foreseeable future, data provided by human raters will continue to play an important role in personality assessment.

Strategy 2: Collect judgment data from multiple sources

Another approach is to collect judgement data on the same target persons from different perceivers (Campbell & Fiske, 1959; Podsakoff et al., 2003). For example, instead of correlating self-reports on scale A with self-reports on scale B, one may correlate self-reports on scale A with informant reports on scale B (or vice versa). If an association between the two assessments is still found using the latter approach, one may interpret it in substantive terms. Unfortunately, the situation is a bit more complicated than that. Multi-source assessment is in fact likely to rule out an inflation of correlations between items that is due to non-substantive variation *between perceivers*, such as formal (Mechanism 5) and attitudinal perceiver-effects (Mechanism 4). It will also rule out an inflation of correlations due to dyadic attitude effects (Mechanism 4). At the same time, however, these same influences may now come to *attenuate* correlations between the different perspectives. Moreover, multi-source assessment will *not* do away with the problem of shared, target-specific halo (Mechanism 4): Some targets may be liked more than other targets, either due to the substantive characteristics that the items of the scale also reflect, or due to other, unknown substantive influences. This would result in an inflation of correlations between assessments, even across data sources. Multi-source assessment will also not control for the problem of semantic redundancy: Even if node A in a

network is assessed by one perceiver and node B is assessed by another perceiver, a possible association between those two nodes may still be rooted in their verbal labels denoting the same facts about the targets. Finally, correlations between perspectives may be inflated by communication between perceivers (Kenny, 1994): Different perceiver may negotiate shared views of the same targets, irrespective of how accurate those views are. For all of these reasons, multi-source assessment will still yield relatively ambiguous results that may not be directly interpreted in terms of associations between underlying substance variables.

Strategy 3: Collect judgment data using items that rule out non-substantial influences

A third, alternative approach is to collect judgment data, but to rule out possible non-substantive influences by way of how the items are phrased or presented. In regard to Mechanism 5, this is very easy: All it takes is a response format that requires all perceivers to exhaust the available response range to the same extent (such as the Q-sort; Block, 2008). With regard to semantic overlap, the situation is considerably more difficult, as this would require an item-set in which all possible pairs of items have first been assessed for semantic redundancy (either by human raters, or in an automatized fashion), and all redundancies were then eliminated. We are not aware of any study that has ever applied such an approach. The possible influence of perceiver attitudes on judgments may be neutralized by having perceivers choose the most fitting item from a set of items with equal social (un-)desirability, but different substantive base (Wetzel & Frick, 2020), or by using items that describe the same substantive base but are balanced in terms of evaluative tone (Borkenau & Ostendorf, 1992; Pettersson et al., 2012). One may also attempt to rephrase items in a way that they reflect only substance, but no evaluation anymore (Bäckström, Björklund & Larsson, 2009). However, although the social desirability of items may easily be assessed in an exact fashion (Edwards, 1953), these approaches still have their difficulties, because (a) most person-descriptive terms from the

natural language *are* strongly evaluative (Anderson, 1968) – so a set of truly neutral items will be difficult to come by, and (b) research showing how the exact same substance dimension (or several, orthogonal substance dimensions) may be assessed using items with different (the same) social desirability is lacking.

Strategy 4: Collect judgment data and quantify non-substantial influences

A fourth, alternative approach is to use judgment data, but then *quantify* the influences of non-substantive influences, and *control* for these when determining associations between items. The pairwise semantic redundancy of items (Mechanism 3) may be assessed using human raters, or in an automatized fashion. The social desirability of items may also be assessed by human raters (Edwards, 1953, 1957), with excellent reliability. Furthermore, perceiver attitudes may be explicitly assessed by simply asking the perceivers how much they like the targets. This has been done numerous times before, and the outcomes have been fairly consistent with what one would expect based on the theoretical analysis presented above (e.g., Leising, Erbs & Fritz, 2010). In the case of self-ratings, an explicit measure of the perceivers/targets' self-esteem will probably do the job. Finally, the perceivers' formal response styles may be assessed by simply averaging their responses across a wide range of ratings. Ideally, these ratings would involve many different targets, and many different items that are balanced in terms of substance, attitude, and semantics. Again, the latter may be difficult to achieve, for the reasons outlined above. Also, it needs to be kept in mind that there may be more than one formal response style. For example, perceivers may differ not only in whether they prefer a specific location on any response scale, but also in whether they prefer to agree or disagree with any statement (acquiescence). The construction of a sufficiently balanced standard measure for assessing perceivers' formal response styles therefore remains an objective for future research.

The relevant characteristics of perceivers, targets, dyads, and items that have been assessed may then be used as covariates in advanced statistical analyses. For example, in factor analysis, one may introduce additional factors that capture the perceivers' tendency to endorse any item regardless of content (acquiescence; Aichholzer, 2014; Maydeu-Olivares & Coffman, 2006), and/or the perceivers' tendency to endorse positive items more than negative items, regardless of content (= attitude) (e.g., Anusic et al., 2009; Pettersson et al., 2012; Wetzel et al., 2015). Likewise, in multilevel profile analyses, correlations between whole profiles of target descriptions (e.g., by the self and others) may be used as the basic unit of analysis, and then be simultaneously predicted from characteristics of the perceiver (e.g., formal response style), the dyad (e.g., Liking), and the items (e.g., social desirability) (Biesanz, 2010; Wessels et al., 2020). An unsolved problem associated with this fourth strategy is the risk of "pouring out the baby with the bathwater" when judgments are partialled for attitudes, but that partialling then removes some of the substance variance of interest, as well. This might happen when the substance that is assessed by the items strongly affects the average perceiver's attitude toward the targets (see Figure 4b). The extent to which this really is a problem is unknown, however, and another valuable objective for future research.

Outlook

Most psychometric research, including research on general factors and network models, relies on correlations between items on which perceivers judge targets. In order to be able to *validly* interpret such correlations in terms of associations between substance variables - which most research aims for - all non-substantive reasons for the emergence of correlations between items have to be ruled out. The person judgment literature has been grappling with the influence of "method factors" for decades, but the present paper is the first to present a comprehensive, formalized account of the issues involved. We hope that this formalized

conceptual framework may help organize future research into these issues better, identify unsolved research questions like the ones we just pointed out, and ultimately improve on the validity of conclusions that psychologists draw from patterns of correlations between items or scales. Given that most contemporary research (e.g., into general factors and network models) still seems to ignore these issues, there is significant room for improvement in that regard.

References

- Achenbach, T. M. (1966). The classification of children's psychiatric symptoms: a factor-analytic study. *Psychological Monographs: general and applied*, 80, 1-37. doi: 10.1037/h0093906
- Aichholzer, J. (2014). Random intercept EFA of personality scales. *Journal of Research in Personality*, 53, 1-4. doi: 10.1016/j.jrp.2014.07.001
- American Psychiatric Association (2013). *Diagnostic and Statistical Manual of Mental Disorders*. (5th ed.). Washington, DC: American Psychiatric Association.
- Anderson, N. H. (1968). Likeableness ratings of 555 personality-trait words. *Journal of Personality and Social Psychology*, 9, 272–279. doi: 10.1037/h0025907
- Anusic, I., Schimmack, U., Pinkus, R. T., & Lockwood, P. (2009). The nature of correlations among big five ratings: The Halo-Alpha-Beta-Model. *Journal of Personality and Social Psychology*, 97, 1142-1156. doi: 10.1037/a0017159
- Arnulf, J. K., Larsen, K. R., Martinsen, O. L., & Bong, C. H. (2014). Predicting survey responses: how and why semantics shape survey statistics on organizational behavior. *PLOS ONE*, 9(9), e106361. doi: 10.1371/journal.pone.0106361
- Bäckström, M., Björklund, F., & Larsson, M. R. (2009). Five-factor inventories have a major general factor related to social desirability which can be reduced by framing items neutrally. *Journal of Research in Personality*, 43, 335–344. doi: 10.1016/j.jrp.2008.12.013
- Bäckström, M., Björklund, F., & Larsson, M. R. (2014). Criterion validity is maintained when items are evaluatively neutralized: evidence from a full-scale five factor model inventory. *European Journal of Personality*, 28, 620-633. doi: 10.1002/per.1960
- Bäckström, M., & Björklund, F. (2016). Is the general factor of personality inventories based on evaluative responding? *Personality and Individual Differences*, 96, 31-35. doi: 10.1016/j.paid.2016.02.058

- Bender, D. S., Morey, L. C., & Skodol, A. E. (2011). Toward a model for assessing level of personality functioning in DSM–5, part I: A review of theory and methods. *Journal of Personality Assessment*, 93, 332–346. doi: 10.1080/00223891.2011.583808
- Bishop, G., Spence, S. H., & McDonald, C. (2003). Can parents and teachers provide a reliable and valid report of behavioral inhibition? *Child Development*, 74(6), 1899–1917.
- Block, J. (1995). A contrarian view of the five-factor approach to personality description. *Psychological Bulletin*, 117, 187–215. doi: 10.1037/0033-2909.117.2.187
- Block, J. (2008). *The Q-sort in character appraisal: Encoding subjective impressions of persons quantitatively*. Washington, DC: American Psychological Association.
- Bono, J. E., & Judge, T. A. (2003). Core self-evaluations: A review of the trait and its role in job satisfaction and job performance. *European Journal of Personality*, 17, 5–18. doi: 10.1002/per.481
- Borgatti, S. P., Mehra, A., Brass, D. J., & Labianca, G. (2009). Network analysis in the social sciences. *Science*, 323(5916), 892–895. doi: 10.1126/science.1165821
- Borkenau, P., & Ostendorf, F. (1989). Descriptive consistency and social desirability in self- and peer reports. *European Journal of Personality*, 3, 31–45. doi: 10.1002/per.2410030105
- Borkenau, P., & Ostendorf, F. (1992). Social desirability scales as moderator and suppressor variables. *European Journal of Personality*, 6(3), 199–214. doi: 10.1002/per.2410060303
- Borsboom, D. & Cramer, A.O.J. (2013). Network analysis: An integrative approach to the structure of psychopathology. *Annual Review of Clinical Psychology*, 9, 91–121. doi: 10.1146/annurev-clinpsy-050212-185608
- Bringmann, L. F., Elmer, T., Epskamp, S., Krause, R. W., Schoch, D., Wichers, M., ... & Snippe, E. (2019). What do centrality measures measure in psychological networks? *Journal of Abnormal Psychology*, 128(8), 892–903. doi: 10.1037/abn0000446

Brunswik, E. (1956). *Perception and the representative design of psychological experiments*.

Berkeley, CA: University of California Press.

Burns, G. N., Morris, M. B., Periard, D. A., LaHuis, D., Flannery, N. M., Carretta, T. R., & Roebke, M. (2017). Criterion-related validity of a Big Five general factor of personality from the TIPI to the IPIP. *International Journal of Selection and Assessment*, 25, 213-222. doi: 10.1111/ijsa.12174

Campbell, D. T., & Fiske, D. W. (1959). Convergent and discriminant validation by the multitrait-multimethod matrix. *Psychological Bulletin*, 56, 81-105. doi: 10.1037/h0046016

Carver, C. S., Johnson, S. L., & Timpano, K. R. (2017). Toward a functional view of the p factor in psychopathology. *Clinical Psychological Science*, 5, 880-889. doi: 10.1177/2167702617710037

Caspi, A., Houts, R. M., Belsky, D. W., Goldman-Mellor, S. J., Harrington, H., Israel, S., ... & Moffitt, T. E. (2014). The p factor: one general psychopathology factor in the structure of psychiatric disorders? *Clinical Psychological Science*, 2, 119-137. doi: 10.1177/2167702613497473

Caspi, A., & Moffitt, T. E. (2018). All for one and one for all: Mental disorders in one dimension. *American Journal of Psychiatry*, 175, 831-844. doi: 10.1176/appi.ajp.2018.17121383

Chang, L., Connelly, B.S. & Geeza, A. A. (2012). Separating method factors and higher order traits of the Big Five: A meta-analytic multitrait-multimethod approach. *Journal of Personality and Social Psychology*, 102, 408-426. doi: 10.1037/a0025559

Cramer, A. O. J., van der Sluis, S., Noordhof, A., Wichers, M., Geschwind, N., Aggen, S. H., Kendler, K. S., & Borsboom, D. (2012). Dimensions of Normal Personality as Networks in Search of Equilibrium: You Can't Like Parties if You Don't Like People. *European Journal of Personality*, 26, 414-431. doi: 10.1002/per.1866

- Danay, E., & Ziegler, M. (2011). Is there really a really a single factor of personality? A multirater approach to the apex of personality. *Journal of Research in Personality, 45*(6), 560-567. doi: 10.1016/j.jrp.2011.07.003
- Davies, S. E., Connelly, B. S., Ones, D. S., & Birkland, A. S. (2015). The General Factor of Personality: The “Big One,” a self-evaluative trait, or a methodological gnat that won’t go away? *Personality and Individual Differences, 81*, 13-22. doi: 10.1016/j.paid.2015.01.006
- Digman, J. M. (1997). Higher-order factors of the Big Five. *Journal of Personality and Social Psychology, 73*, 1246-1256. doi: 0.1037/0022-3514.73.6.1246
- Dumas, J. E., Johnson, M., & Lynch, A. M. (2002). Likableness, familiarity, and frequency of 844 person-descriptive words. *Personality and Individual Differences, 32*, 523–531. DOI: 10.1016/S0191-8869(01)00054-X
- Edwards, A. L. (1953). The relationship between the judged desirability of a trait and the probability that the trait will be endorsed. *Journal of Applied Psychology, 37*, 90-93. doi: 10.1037/h0058073
- Edwards, A. L. (1957). *The social desirability variable in personality assessment and research*. New York, NY: The Dryden Press.
- Eid, M., & Diener, E. (2004). Global judgments of subjective well-being: Situational variability and long-term stability. *Social Indicators Research, 65*(3), 245-277.
- Elliott, H., Jones, P. J., & Schmidt, U. (2018). Central symptoms predict post-treatment outcomes and clinical impairment in anorexia nervosa: A network analysis. *Clinical Psychological Science, 8*(1), 139-154. doi: 10.1177/2167702619865958
- Epskamp, S., Borsboom, D., & Fried, E. I. (2018). Estimating psychological networks and their accuracy: A tutorial paper. *Behavior Research Methods, 50*(1), 195-212. doi: 10.3758/s13428-017-0862-1

- Epskamp, S., & Fried, E. I. (2018). A tutorial on regularized partial correlation networks. *Psychological methods*, 23(4), 617-634. doi: 10.1037/met0000167
- Fried, E. I., & Cramer, A. O. (2017). Moving forward: challenges and directions for psychopathological network theory and methodology. *Perspectives on Psychological Science*, 12(6), 999-1020. doi: 10.1177/1745691617705892
- Fried, E. I., Epskamp, S., Nesse, R. M., Tuerlinckx, F., & Borsboom, D. (2016). What are 'good' depression symptoms? Comparing the centrality of DSM and non-DSM symptoms of depression in a network analysis. *Journal of Affective Disorders*, 189, 314-320. doi: 10.1016/j.jad.2015.09.005
- Furr, R. M., & Funder, D. C. (1998). A multimodal analysis of personal negativity. *Journal of Personality and Social Psychology*, 74, 1580–1591. doi: 10.1037/0022-3514.74.6.1580
- Garcia, D., Rosenberg, P., Al Nima, A., Granjard, A., Cloninger, K. M., & Sikström, S. (2020). Validation of two short personality inventories using self-descriptions in natural language and quantitative semantics test theory. *Frontiers in Psychology*, 11, 16. doi: 10.3389/fpsyg.2020.00016
- Gosling, S. D., Ko, S. J., Mannarelli, T., & Morris, M. E. (2002). A room with a cue: Personality judgments based on offices and bedrooms. *Journal of Personality and Social Psychology*, 82, 379-398. doi: 10.1037//0022-3514.82.3.379
- Gräf, M., & Unkelbach, C. (2016). Halo effects in trait assessment depend on information valence: Why being honest makes you industrious, but lying does not make you lazy. *Personality and Social Psychology Bulletin*, 42, 290–310. doi: 10.1177/0146167215627137
- Hampson, S. E., John, O. P., & Goldberg, L. R. (1986). Category breadth and hierarchical structure in personality: Studies of asymmetries in judgments of trait implications. *Journal of Personality and Social Psychology*, 51, 37–54. doi:10.1037/0022-3514.51.1.37

- Irwing, P. (2013). The general factor of personality: Substance or artefact? *Personality and Individual Differences*, 55, 234-242. doi: 10.1016/j.paid.2013.03.002
- Jahng, S., Trull, T. J., Wood, P. K., Tragesser, S. L., Tomko, R., Grant, J. D., ... & Sher, K. J. (2011). Distinguishing general and specific personality disorder features and implications for substance dependence comorbidity. *Journal of Abnormal Psychology*, 120(3), 656-669. doi: 10.1037/a0023539
- Jones, P.J. (2018). networktools: Tools for identifying important nodes in networks [Computer software]. Retrieved from <https://CRAN.Rproject.org/package=networktools>
- Judge, T. A., Erez, A., Bono, J. E., & Thoresen, C. J. (2002). Are measures of self-esteem, neuroticism, locus of control, and generalized self-efficacy indicators of a common core construct? *Journal of Personality and Social Psychology*, 83, 693–710. doi: 10.1037/0022-3514.83.3.693
- Kanfer, F. H., & Saslow, G. (1969). Behavioral diagnosis. In C. M. Franks (Ed.), *Behavior therapy: Appraisal and status* (pp. 417–444). New York, NY: McGraw-Hill.
- Kanfer, F. H., & Schmelzer, D. (2005). *Wegweiser Verhaltenstherapie: Psychotherapie als Chance* [Guide for behavior therapy: Psychotherapy as opportunity] (2nd ed.). Heidelberg, Germany: Springer.
- Kenny, D. A. (1994). *Interpersonal perception. A social relations analysis*. New York, NY: The Guilford Press.
- Kenny, D. A. (2004). PERSON: A general model of interpersonal perception. *Personality and Social Psychology Review*, 8, 265-280. doi: 10.1207/s15327957pspr0803_3
- Lahey, B. B., Applegate, B., Hakes, J. K., Zald, D. H., Hariri, A. R., & Rathouz, P. J. (2012). Is there a general factor of prevalent psychopathology during adulthood? *Journal of Abnormal Psychology*, 121, 971. doi: 10.1037/a0028355

- Lance, C. E., LaPointe, J. A., & Fisicaro, S. A. (1994). Tests of three causal models of halo rater error. *Organizational Behavior and Human Decision Processes*, 57, 83-96. doi: 10.1006/obhd.1994.1005
- Leising, D., Erbs, J., & Fritz, U. (2010). The letter of recommendation effect in informant ratings of personality. *Journal of Personality and Social Psychology*, 98, 668-682. doi: 10.1037/a0018771
- Leising, D., Gallrein, A.-M.B., & Dufner, M. (2014). Judging the behavior of people we know: Objective assessment, confirmation of pre-existing views, or both? *Personality and Social Psychology Bulletin*, 40, 153-163. doi: 10.1177/0146167213507287
- Leising, D., Locke, K., Kurzius, E., & Zimmermann, J. (2016). Quantifying the association of self-enhancement bias with self-ratings of personality and life satisfaction. *Assessment*, 23, 588-602. doi: 10.1177/1073191115590852
- Leising, D., Ostrovski, O., & Borkenau, P. (2012). Vocabulary for describing disliked persons is more differentiated than vocabulary for describing liked persons. *Journal of Research in Personality*, 46, 393-396. doi.org/10.1016/j.jrp.2012.03.006
- Leising, D., Ostrovski, O., & Zimmermann, J. (2013). Are we talking about the same person here? Inter-rater agreement in judgments of personality varies dramatically with how much the perceivers like the targets. *Social Psychological and Personality Science*, 4, 468-474. doi: 10.1177/1948550612462414
- Leising, D., Scherbaum, S., Locke, K., & Zimmermann, J. (2015). A model of "substance" and "evaluation" in person judgments. *Journal of Research in Personality*, 57, 61-71. doi: 10.1016/j.jrp.2015.04.002
- Leising, D., Scherbaum, S., Packmohr, P., & Zimmermann, J. (2018). Substance and evaluation in personality disorder diagnoses. *Journal of Personality Disorders*, 32, 766-783. doi: 10.1521/pedi_2017_31_324

Leising, D., Vogel, D., Waller, V., & Zimmermann, J. (under review). Correlations between items may be predicted from the product of their centered social desirability ratings.

Leising, D., & Zimmermann, J. (2011). An integrative conceptual framework for assessing personality and personality pathology. *Review of General Psychology, 15*, 317-330. doi: 10.1037/a0025070

Lunansky, G., van Borkulo, C. D., & Boersboom, D. (2019). Personality, resilience, and psychopathology: a model for the interaction between slow and fast network processes in the context of mental health.

Maydeu-Olivares, A., & Coffman, D. L. (2006). Random intercept item factor analysis. *Psychological Methods, 11*(4), 344–362. doi: 10.1037/1082-989X.11.4.344

Musek, J. (2007). A general factor of personality: Evidence for the Big One in the five-factor model. *Journal of Research in Personality, 41*, 1213-1233. doi: 10.1016/j.jrp.2007.02.003

Nisbett, R. E., & Wilson, T. D. (1977). The halo effect: Evidence for unconscious alteration of judgments. *Journal of Personality and Social Psychology, 35*, 250-256. doi: 10.1037/0022-3514.35.4.250

Oltmanns, J. R., Smith, G. T., Oltmanns, T. F., & Widiger, T. A. (2018). General factors of psychopathology, personality, and personality disorder: Across domain comparisons. *Clinical Psychological Science, 6*, 581-589. doi: 10.1177/2167702617750150

Peabody, D. (1967). Trait inferences: Evaluative and descriptive aspects. *Journal of Personality and Social Psychology, 7*, 1–18. doi: 10.1037/h0025230

Pelt, D. H., van der Linden, D., Dunkel, C. S., & Born, M. P. (2017). The general factor of personality and job performance: Revisiting previous meta-analyses. *International Journal of Selection and Assessment, 25*, 333-346. doi: 10.1111/ijsa.12188

- Pettersson, E., Turkheimer, E., Horn, E. E., & Menatti, A. R. (2012). The general factor of personality and evaluation. *European Journal of Personality, 26*, 292-302. doi: 10.1002/per.839
- Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*, 879–903. doi: 10.1037/0021-9010.88.5.879
- Revelle, W., & Wilt, J. (2013). The general factor of personality: A general critique. *Journal of Research in Personality, 47*, 493-504. doi: 10.1016/j.jrp.2013.04.012
- Riemann, R., & Kandler, C. (2010). Construct validation using multitrait-multimethod-twin data: The case of a General Factor of Personality. *European Journal of Personality, 24*, 258-277. doi: 10.1002/per.760
- Robinaugh, D. J., Hoekstra, R. H., Toner, E. R., & Borsboom, D. (2020). The network approach to psychopathology: a review of the literature 2008–2018 and an agenda for future research. *Psychological Medicine, 50*(3), 353-366.
- Rushton, J. P., & Irwing, P. (2011). The general factor of personality. In T. Chamorro-Premuzic, S. von Stumm, & A. Furnham (Eds.), *The Wiley-Blackwell handbook of individual differences* (pp. 132-161). New York, NY: Blackwell Publishing.
- Saucier, G. (1994). Separating description and evaluation in the structure of personality attributes. *Journal of Personality and Social Psychology, 66*, 141-154. doi: 10.1037/0022-3514.66.1.141
- Schmittmann, V. D., Cramer, A. O. J., Waldorp, L. J., Epskamp, S., Kievit, R. A., & Borsboom, D. (2013). Deconstructing the construct: A network perspective on psychological phenomena. *New Ideas in Psychology, 31*, 43-53. doi: 10.1016/j.newideapsych.2011.02.007

Sharp, C., Wright, A. G., Fowler, J. C., Frueh, B. C., Allen, J. G., Oldham, J., & Clark, L. A. (2015).

The structure of personality pathology: Both general ('g') and specific ('s') factors? *Journal of Abnormal Psychology*, 124, 387. doi: 10.1037/abn0000033

Sikström, S., & Garcia, D. (2019). *Statistical semantics – methods and applications*. Cham: Springer.

Spearman, C. (1904). "General Intelligence" objectively determined and measured. *The American Journal of Psychology*, 15, 201-292. doi: 10.2307/1412107

Srivastava, S., Guglielmo, S., & Beer, J. S. (2010). Perceiving others' personalities: Examining the dimensionality, assumed similarity to the self, and stability of perceiver effects. *Journal of Personality and Social Psychology*, 98, 520-534. doi: 10.1037/a0017057

Stachl, C., Au, Q., Schoedel, R., Buschek, D., Voelkl, S. T., ... & Buehner, M. (in press). Behavioral patterns in smartphone usage predict Big Five personality traits. doi: 10.31234/osf.io/ks4vd

Stone, A. A., & Shiffman, S. (1994). Ecological momentary assessment (EMA) in behavioral medicine. *Annals of Behavioral Medicine*, 16, 199-202. doi: 10.1093/abm/16.3.199

Tackett, J. L., Lahey, B. B., Van Hulle, C., Waldman, I., Krueger, R. F., & Rathouz, P. J. (2013). Common genetic influences on negative emotionality and a general psychopathology factor in childhood and adolescence. *Journal of Abnormal Psychology*, 122, 1142. doi: 10.1037/a0034151.

Thorndike, E. L. (1920). A constant error in psychological ratings. *Journal of Applied Psychology*, 4, 25-29. doi: 10.1037/h0071663

van der Linden, D., te Nijenhuis, J., & Bakker, A. B. (2010). The general factor of personality: A meta-analysis of Big Five intercorrelations and a criterion-related validity study. *Journal of Research in Personality*, 44, 315-327. doi: 10.1016/j.jrp.2010.03.003

- van der Maas, H. L. J., Dolan, C. V., Grasman, R. P. P. P., Wicherts, J. M., Huizenga, H. M., & Raijmakers, M. E. J. (2006). A dynamical model of general intelligence: the positive manifold of intelligence by mutualism. *Psychological Review*, 113(4), 842-861. doi: 10.1037/0033-295X.113.4.842
- Viswesvaran, C., Schmidt, F. L., & Ones, D. S. (2005). Is there a general factor in ratings of job performance? A meta-analytic framework for disentangling substantive and error influences. *Journal of Applied Psychology*, 90(1), 108-131. doi: 10.1037/0021-9010.90.1.108
- Wessels, N. W., Zimmermann, J., Biesanz, J. C., & Leising, D. (in press). Differential associations of knowing and liking with accuracy and positivity bias in person perception. *Journal of Personality and Social Psychology*. doi: 10.17605/OSF.IO/5DG94
- West, T. V., & Kenny, D. A. (2011). The truth and bias model of judgment. *Psychological Review*, 118, 357–378. doi: 10.1037/a0022936
- Wetzel, E., Carstensen, C. H., & Böhnke, J. R. (2013). Consistency of extreme response style and non-extreme response style across traits. *Journal of Research in Personality*, 47, 178-189. doi: 10.1016/j.jrp.2012.10.010
- Wetzel, E., & Frick, S. (2020). Comparing the validity of trait estimates from the multidimensional forced-choice format and the rating scale format. *Psychological Assessment*, 32(3), 239–253. doi: 10.1037/pas0000781
- Wetzel, Lüdtke, O., Zettler, I., & Böhnke, J. R. (2015). The stability of extreme response style and acquiescence over 8 years. *Assessment*, 23, 279-291. doi: 10.1177/1073191115583714
- Wright, A. G. C., Hopwood, C. J., Skodol, A. E., Morey, L. C. (2016). Longitudinal validation of general and specific features of personality pathology. *Journal of Abnormal Psychology*, 125(8), 1120-1134. doi: 10.1037/abn0000165

- Wood, D., Harms, P., & Vazire, S. (2010). Perceiver effects as projective tests: what your perceptions of others say about you. *Journal of Personality and Social Psychology*, 99, 174-190. doi: 10.1037/a0019390
- Wood, D., Hensler Gardner, M., & Harms, P. D. (2015). How functionalist and process approaches to behavior can explain trait covariation. *Psychological Review*, 122, 84-111. doi: 10.1037/a0038423

Contributions

This is a conceptual / review paper. All authors contributed significantly to internal discussions of the core issues, as well as to the writing itself.

Competing Interests

The corresponding author declares, on behalf of all five authors, that no competing interests of any kind are associated with this work.