Science Self-Concept – More Than the Sum of its Parts?

Ulrich Schroeders

Psychological Assessment, University of Kassel

Malte Jansen

Institute for Educational Quality Improvement, Berlin, Germany

Centre for International Student Assessment, Germany

Author Note

Ulrich Schroeders, Department of Psychology, University of Kassel, Germany; Malte Jansen, Institute for Educational Quality Improvement (IQB), Berlin, Germany, and Centre for International Student Assessment (ZIB), Germany.

Correspondence concerning this article should be addressed to Ulrich Schroeders, Psychological Assessment, Institute of Psychology, University of Kassel, Holländische Str. 36-38, 34127 Kassel, Germany, E-mail: schroeders@psychologie.uni-kassel.de

This research was supported by a grant from the *Deutsche Forschungsgemeinschaft* (DFG) to Ulrich Schroeders and Andrea Hildebrandt (SCHR 1591/1-1 and HI 1780/4-1) as part of the Priority Program 1646 “*Education as a Lifelong Process*”. We thank the research data center (FDZ) at the Institute for Educational Quality Improvement (IQB) for providing data access.

Abstract

Academic self-concept is understood as a multidimensional, hierarchical construct. Multidimensionality refers to the subject-specific differentiation of academic self-concepts, whereas hierarchy refers to the aggregation of more specific facets of self-concepts into more general ones. Previous research demonstrated that students distinguish between their self-concepts in biology, chemistry, and physics if taught as separate school subjects, as is done in Germany. However, large-scale international educational studies, such as PISA, often use a monolithic science self-concept measure. It is yet unclear whether an aggregate of subject-specific self-concepts is equivalent to a directly measured science self-concept. We assessed the subject-specific and a general science self-concept of 1,232 German grade 10 students. A higher-order factor model and a bifactor model demonstrated a very high correlation between the “inferred” and the explicitly assessed general science self-concept. Despite the high empirical overlap, we argue for a more nuanced view of the science self-concept, because statistical unity is not to be confused with causal unity. Moreover, from a methodological perspective, we used multi-group confirmatory factor analysis to examine the mean structure and local weighted structural equation models to study measurement invariance across science ability. Implications for the theoretical status of self-concept as a hierarchical construct are discussed.

Keywords: STEM, Science self-concept, dimensionality, gender differences, psychometrics

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1. Introduction

The academic self-concept—the self-perception of one's ability in an academic domain—is an important motivational factors in educational psychology (Marsh, Martin, Yeung, & Craven, 2017; Marsh et al., 2018; Steinmayr & Spinath, 2009). Students who are confident in their academic ability are also more motivated and get better grades, which in turn increases their self-concept (Chen, Yeh, Hwang, & Lin, 2013; Guo, Marsh, Parker, Morin, & Dicke, 2017; Huang, 2011; Nagengast et al., 2011; Trautwein, Lüdtke, Schnyder, & Niggli, 2006; Valentine, DuBois, & Cooper, 2004). Furthermore, domain-specific academic self-concepts show effects on educational decisions such as course selection (Nagy, Trautwein, Baumert, Köller, & Garrett, 2006; Marsh & Yeung, 1997a, 1997b), career aspirations (e.g., Lauermann, Tsai, & Eccles, 2017), and choice of study (Musu-Gillette, Wigfield, Harring, & Eccles, 2015; Parker et al., 2012). This pattern is also found in the sciences, which are considered particularly important from a policy perspective as part of the STEM field: students with higher self-concepts have been shown to be more likely to aspire towards a career in science (Guo et al., 2017; Nagengast & Marsh, 2012; Taskinen, Schütte, & Prenzel, 2013). In this study, we address open questions related to the assessment and modeling of academic self-concepts in science.

1.1 The Structure of Self-Concept in the Sciences

The Shavelson model (Shavelson, Hubner, & Stanton, 1976), one of the first influential models on the organization and internal representation of self-concepts, introduces the assumption of self-concepts as multidimensional (i.e., horizontally-organized) and hierarchically (i.e., vertically-organized) constructs. With respect to its multidimensionality, several self-concepts can be distinguished: for example, on a broad level an academic, a social, an emotional,

and a physical self-concept. With respect to its hierarchy, it is possible to distinguish different layers of self-concept, which corresponds to its granularity and specificity. In educational psychology, self-concept is most commonly studied at the level of school subjects, such as mathematics, English, and science (e.g., Marsh, 1990). However, it is also possible that students develop a more fine-grained self-concept: at the level of different language skills for example, self-concepts for reading, writing, listening, and speaking can develop within the verbal self-concept (Arens & Jansen, 2016), and even more fine-grained at the level of text genres within the reading self-concept (Henschel, Roick, Brunner, & Stanat, 2013).

While the notion of multidimensional organization has been repeatedly supported (Brunner et al., 2010; Huang, 2011; Marsh, 1990; Marsh & Craven, 2006; Valentine, DuBois, & Cooper, 2004), empirical results have questioned the assumption of hierarchy, at least for a general academic self-concept. Instead it has been demonstrated that the subject-specific self-concept factors in mathematics and the language of instruction are almost uncorrelated, although the respective abilities of students are highly correlated (Marsh, 1986; Marsh, Byrne, & Shavelson, 1988). Such a pattern is contrary to the idea of a general academic self-concept factor affecting all domain-specific self-concepts. This led to the development of the Marsh/Shavelson model (Marsh, 1990; Marsh & Shavelson, 1985; Marsh et al., 1988), which discards the idea of a general factor in favor of two uncorrelated factors—a general mathematical and a general verbal self-concept—that may form the endpoints on a continuous dimension. Although the assumption of a general overarching academic self-concept has been dismissed, some studies evaluated the hierarchy within the language domain (Arens & Jansen, 2016; Lau, Yeung, Jin, & Low, 1999; Yeung, Chui, Lau, McInerney, & Russell-Bowie, 2000). For example, Arens and Jansen (2016) examined the relation between a higher-order, “inferred” verbal self-concept comprised of

speaking, listening, writing, and reading and a directly assessed global self-concept in three different languages (German, English, and French). The authors found correlations ranging between .85 (German, sample's native language) and .95 (English/French, first foreign language) which were interpreted as evidence for the hierarchical nature of language self-concepts, while simultaneously systematic gender differences in the first-order factor means were interpreted as indication for the multidimensional nature of language self-concepts.

Comparatively few studies deal with the self-concept in the sciences at all and often at a very general level (e.g., Chiu, 2008, 2012) because the focus in many countries such as the US is on integrated science teaching, although different branches of science are conveyed (e.g., physical, life, earth, space, and human sciences). Nonetheless, the science self-concept in the Marsh/Shavelson model (Marsh, 1990; see also Brunner et al., 2010) is not conceptualized as a single self-concept, but it is split into a physics-related facet, which is solely related to a higher-order mathematics-and-science factor, and a biology-related facet, which takes on an intermediate position between a mathematical and a verbal second-order self-concept factor. In countries such as Germany, the natural sciences of biology, chemistry, and physics are taught as separate subjects, presumably out of pedagogical tradition (e.g., Hardy, 2014; Jansen, Schroeders, & Lüdtke, 2014). Previous research has demonstrated that—although the achievement data across science subjects are highly correlated—the self-concepts in science are only moderately related between $\rho(\text{biology, physics}) = .34$ and $\rho(\text{chemistry, physics}) = .49$ (Jansen et al., 2014). The differentiation of self-concepts in science can be linked to the way of teaching and the feedback students receive for their achievement. In cases where students learn science as separate subjects which are individually graded, the correlations are considerably lower than when science is taught as integrated subject (Jansen, Schroeders, Lüdtke, & Marsh,

2019). In a comprehensive study, Hardy (2014) juxtaposed the self-concepts in biology, chemistry, and physics together with self-concepts for two overarching concepts—“scientific enquiry” and “nature of science” and modeled atop a second-order science concept factor. The high correlation between the second-order self-concept factor and a directly measured global self-concept amounted to $\rho = .87$, which was interpreted as empirical evidence for the hierarchical nature of the academic self-concepts in science.

1.2 Assessing and Modeling Science Self-Concept

The general self-concept in science can be operationalized, assessed, and modeled in different ways. On the level of operationalizing the construct, a general science self-concept can be measured with global, domain-unspecific items (e.g., “I’m good in sciences.”) or with domain-specific items (e.g., “I’m good in biology/chemistry/physics.”), which are somehow aggregated to compose an inferred general self-concept. The question arises to what extent the way we assess and model science self-concept affects our conclusions about the structure of science self-concept and its relation to other variables. Thus, we compare the directly measured general science self-concept with other techniques to model the structure of science self-concept based on the domain-specific self-concepts. In the following, we explain the theoretical assumptions and meaning of the modeling techniques, that is, a higher-order factor model and a bifactor factor model.

A higher-order factor model captures the communality of the different science self-concept factors in a second-order factor (Figure 1, Model 2). In the case of three first-order self-concept factors (i.e., in biology, chemistry, and physics), such a model is mathematically identical to a three-dimensional model, if no additional covariates or constraints are introduced. However, a *correlated factor model* (Figure 1, Model 1) does not measure a common target

dimension (i.e., science self-concept), whereas the higher-order model provides a measurement structure to the factor correlations (see also Reise, Moore, & Haviland, 2010). That means, the second-order factor as the target dimension depicts the common variance (*communality*) between the first-order factors. Higher-order models are sometimes used in intelligence research (see also Schulze, 2004) to capture the high communality between cognitive tasks—a phenomenon which is also known as *positive manifold* (van der Maas et al., 2006). However, as shown previously with the Marsh/Shavelson model, the assumption of high commonality is not met in self-concept research if subjects that are perceived differently by students are included. While the self-concepts in math and language presumably represent the poles of an academic self-concept continuum (Marsh, 1990), science self-concepts are at least moderately positively correlated (Jansen et al., 2014), which might qualify for a higher-order self-concept factor. Differently put, due to these at least moderate positive correlations between the different science domains, it seems sensible to assess a global science self-concept.

A *bifactor model* includes a general factor reflecting the common variance of all items and specific factors (often called group factors) that cover additional variance among sets of items. The general and the specific factor should be uncorrelated or orthogonal (see Figure 1, Model 3), which is why bifactor models are also called nested factor models. Conceptually, the general factor represents the target construct, while the nested factors represent more narrow subdomain constructs. Thus, as Reise (2012, p. 668) pointed out, bifactor modeling “appears ideally suited for representing the construct-relevant multidimensionality that arises in the responses to measures of broad constructs where multiple and distinct domains of item content are included to increase content validity”. Bifactor models were initially invented in intelligence research (Holzinger & Swineford, 1937), but have recently experienced a renaissance as an

important structural representation of multidimensionality besides the often used correlated factor model in various areas of assessment (Reise, Moore, & Haviland, 2010; Reise, 2012). They have also been used in self-concept research (see nested Marsh/Shavelson model in Brunner et al, 2010, Schmidt et al., 2017). Please note that there is a direct link between the higher-order and the bifactor model: by means of the Schmid-Leiman decomposition (Schmid & Leiman, 1957), the higher-order factor model converts to a constrained version of the bifactor model with nested factors for the previously first-order factors (Mulaik & Quartetti, 1997). This is achieved by imposing proportionality constraints on the factor loadings in the bifactor model.

1.3 The Present Study

The present article compares two different ways of measuring the general science self-concept: as a directly assessed global science self-concept (e.g., “I’m good in the natural sciences.”) and as a combination of subject-specific self-concepts (e.g., “I’m good in biology/chemistry/physics). The aggregation or combination of the subject-specific science self-concepts can be accomplished in two ways—by modeling a second-order factor vs. a general factor in a bifactor model. If the assumption of perfect hierarchical nature of self-concepts by Shavelson et al. (1976) was valid and, given that biology, chemistry, and physics are the relevant science domains in the German educational system, the correlation between a domain-general self-concept and a higher-order or general factor should approach 1 (see dashed lines in Figure 1). From the perspective of interindividual differences, one is inclined to think that if the correlation reaches unity, then there are no differences in the measures and that a more general self-concept can be split into more specific ones (i.e., the whole being equal to the sum of its parts). However, this statement is imperfect in several ways. First, correlation is not be confused with causation. As Markus and Borsboom (2013, p. 149) put it, “causal unidimensionality

constitutes a stronger claim than mere statistical unidimensionality”. This seemingly philosophical notion is more tangible when one thinks about a hypothetical educational program that fosters a domain-specific self-concept, say, in a physics class. If the intervention is successful, the corresponding self-concept changes, without necessarily changing the general science self-concept: the general science self-concept is not defined by its part. Second, a correlation between differently-measured science self-concept is about the bivariate relationship not about potential mean differences across subgroups. Previous literature showed that gender differences in the science self-concepts are heterogeneous on a subject level, that means no substantial difference was found within biology, but a substantial difference was found within physics (Jansen et al., 2014, 2019). To examine the effect of assessment and modeling on the mean structure, we apply *Multiple-Group Mean and Covariance Structure* (MGMCS) analyses. MGMCS are frequently used to study the influence of categorical moderators (e.g., gender groups or school types) on parameter estimates in *Structural Equation Modeling* (SEM), which leads to the third point—measurement invariance. Even if the correlation between the different assessment methods is 1 in the overall sample, that does not mean that the correlation is fixed or invariant across potential moderators. We double-check the implicit assumption of measurement invariance and test whether the correlation changes depending on the ability in science. Therefore, we used a recently-developed SEM technique, *Local Weighted Structural Equation Modeling*—which will be explained in more detail in the method section—to scrutinize the variance–covariance structure over a continuous context variable.

2. Method

2.1 Design and Participants

The data were collected in a pilot study in the context of the *German National Assessment Studies*, a program of large-scale educational assessment studies in math and the sciences in Germany that compares students' achievement across federal states and against the national educational standards in regular intervals (Pant et al., 2013). Aims and scope of the monitoring program are comparable to the *National Assessment of Educational Progress* (NAEP). Besides pilot testing a pool of newly-developed science items in the content area of *argumentation* and *communication* (Heitmann, Hecht, Scherer, & Schwanewedel, 2017), questionnaires were administered in a balanced incomplete block design (Gonzalez & Rutkowski, 2010). In total, the sample of the pilot study consisted of 3,258 students in 85 schools (including all school types) at the end of secondary school, who were sampled with a two-stage sampling procedure. In the first stage, half of all 16 German federal states were selected so that the heterogeneity across states was covered. In the second stage, schools within each state and two tenth grade classes within these schools were randomly selected. Participation was mandatory at the school level, but students could opt-out of the study. The participation rate at the student level was 79.6%. Students were neither rewarded nor graded in any way. Analyses presented in this paper were based on a subsample of 1,232 students from 48 schools who completed science self-concept questionnaire. All common school types from the German secondary school system were included in the analysis sample with an oversampling of the academic-track *Gymnasium* (50.8%). The remaining school types included vocational-track and mixed-track schools. Mean age was 15.2 years ($SD = 0.91$; $n = 1,231$), and half of the sample was female (52.3%).

2.2 Measures

The self-concepts in biology, chemistry, physics, and science in general were assessed using four items per domain that were shown to be highly reliable in the *Programme for International Student Assessment* (PISA) 2006 study (OECD, 2009) and that are frequently used in other self-concept research (e.g., Nagengast & Marsh, 2012; Nagengast et al., 2011). The original items assessed a general science subject and were modified to match the three science subjects that are the mandatory part of the curricula in secondary school (i.e., biology, chemistry, and physics). The procedure has also been used in previous studies (Möller, Streblow, & Pohlmann, 2006; Schilling, Sparfeldt, & Rost, 2006). Except for the subject-specific modification, the same wording was used, for example, "In biology/chemistry/physics/science, I learn quickly." Students had to indicate their agreement on a five-point scale. For the item wording and descriptives see supplement in the online repository (see below).

2.3 Statistical Analyses

Confirmatory Factor Analyses (CFA) were conducted to test the competing measurement models using the maximum likelihood estimator with robust estimation of standard errors (MLR) because simulation studies provide evidence that categorical variables with five or more categories can be handled as continuous when not heavily skewed (Beauducel & Herzberg, 2006; Rhemtulla, Brosseau-Liard, & Savalei, 2012). Because the χ^2 -statistic is overly sensitive even to trivial model misfit when the sample size is large, we applied a two-index presentation strategy (Hu & Bentler, 1999) that combines an incremental fit index such as the *Comparative Fit Index* (CFI) and an absolute fit index such as the *Root Mean Square Error of Approximation* (RMSEA) to evaluate model fit. The following values were considered to indicate good model fit: CFI $\geq .95$, RMSEA $\leq .08$. Overall, the missingness on the self-concept items was negligible ($M = 1.18$

[0.57; 2.44]). Nonetheless, all models were estimated using the *Full Information Maximum Likelihood* (FIML) procedure (Schafer & Graham, 2002), which results in unbiased estimates under the assumption of *Missingness At Random* (MAR), while retaining statistical power because no observations were deleted (Enders, 2010). We provide the data set, all syntax files, and additional analyses within the Open Science Framework (Soderberg, 2018) at https://osf.io/zj87n/?view_only=7dcaa15829a446428c68991e50b9b97a to make the analyses transparent and reproducible (Nosek et al., 2015). All analyses were conducted with R 3.4.4 (R Development Core Team, 2018), mainly with the R package *lavaan* 0.6-3 (Rosseel, 2012).

To study potential gender differences in the factor means, we used measurement invariance testing with *Multiple-Group Mean and Covariance Structure* (MGMCs, Millsap, 2011), which often follows a straightforward procedure of four hierarchical nested steps of constraining certain measurement parameters to equality across groups (Vandenberg & Lance, 2000; Schroeders & Gnabms, 2019). The basic logic behind the procedure is that, if the additionally introduced restrictions lead to a deterioration in model fit, then the assumption of invariance at this stage is violated. In the first step, *configural MI*, all model parameters are freely estimated across groups except those that are necessary for identification. For *metric MI*, the factor loadings are constrained to invariance across groups allowing for comparisons of bivariate relations (i.e., correlations and regressions). As mentioned, the comparability of the variance-covariance structure is often not sufficient, which is why in the third step, *scalar MI*, also the intercepts are set to be invariant in addition to the factor loadings. Scalar invariance is a necessary prerequisite for meaningful comparison of the factor means across groups. In the last step, *strict MI*, on top of all previous restrictions, the item residuals are constrained to be equal across groups. Based on recommendations in the literature (Cheung & Rensvold, 2002), we

consider a difference in $\Delta CFI > .01$ between two consecutive models as serious deterioration in model fit in measurement invariance testing. Essentially, the measurement invariance testing procedure in a second-order factor models follows the same basic logic, but comprises of more steps since measurement parameters across two layers need to be equated (Chen, Sousa, & West, 2005).

Local weighted structural equation modeling. *Local weighted structural equation modeling* (LSEM; Hildebrandt, Lüdtke, Robitzsch, Sommer, & Wilhelm, 2016; Hildebrandt, Wilhelm, & Robitzsch, 2009) is a recently-developed method in the framework of SEM, which allows the study of measurement parameters depending on a continuous context variable such as age. We examine the correlation between the general science self-concept and the domain-specific, aggregated science self-concept over the science achievement. Science achievement in this study was the mean of the subject-specific *Weighted Likelihood Estimates* (WLEs; Warm, 1989) which derived from three unidimensional, one-parameter logistic models. The most common practice of studying moderating effects of continuous context variables is to categorize the variable that is continuous in nature and use MGMCS. However, there are several conceptual and statistical issues rendering it subpar (see also MacCallum, Zhang, Preacher, & Rucker, 2002). First, building subgroups increases the risk of overlooking nonlinear trends and interaction effects (Hildebrandt et al., 2016). Second, categorization leads to a loss in information on individual differences within a given group, that is, variation within those groups cannot be detected. Third, setting cutoffs and cutting a distribution of a moderator into several parts is frequently arbitrary, which can influence the results (Hildebrandt et al., 2009; MacCallum et al., 2002). In short, there are several advantages in using LSEM to study measurement invariance depending on a continuous moderator variable.

Technically, LSEMs are traditional SEMs that weight observations around focal points (i.e., specific values of the continuous moderator variable) with a kernel function. The core idea is that observations near the focal point provide more information for the corresponding SEM than more distant observations. Observations exactly at the focal point receive a weight of 1, whereas observations with moderator values higher or lower than the focal point receive smaller weights. After calculating the sample weights, the SEM model of interest will be fitted at each focal point within a defined moderator range, so that it is possible to explore trajectories of the model parameters along the continuous moderator. The method is explained in more detail in Hildebrandt et al. (2016) or in a tutorial on LSEM (Olaru, Schroeders, Hartung, & Wilhelm, 2019). All LSEM were estimated with the R package *sirt* (Robitzsch, 2019).

3. Results

Descriptive statistics for the four self-concept scales are listed in Table 1. With values between -0.50 and 0.10 for skewness and -0.93 and 0.01 for kurtosis, univariate normality could be assumed (see Kline, 2015). Both the internal consistencies and the composite reliabilities (ω ; McDonald, 1999) were excellent (biology: $\alpha = .93$, $\omega = .93$; chemistry: $\alpha = .95$, $\omega = .95$; physics: $\alpha = .94$, $\omega = .94$, science: $\alpha = .94$, $\omega = .94$). As indicated by the *intraclass correlations* (ICCs), most of the self-concept variance was located on the individual rather than the class or school level. This is consistent with the assumption that students evaluate their ability mainly within the social reference frame of their class (Marsh, 1987).

3.1 Measurement Models of the Self-Concepts in Science

We estimated the correlated factor model with three subject-specific and the general science self-concept as a baseline model. From a theoretical perspective, such a model circumvents the intended hierarchical structure and is mainly used to acquaint the reader with the

data. In contrast to the CFI, the RMSEA does not indicate sufficient model fit (see Table 1). A correlated factor model with residual correlations between all items with parallel wording (e.g., “I learn quickly in biology” and “I learn quickly in chemistry”)—also known as *Correlated Trait Correlated Uniqueness* model (CTCU, Kenny, 1976; Marsh & Grayson, 1995)—fitted the data significantly better ($\Delta\chi^2(24, N = 1,232) = 427.0; p < .001$). Accordingly, all subsequent models were specified with residual correlations between parallel worded items.

The higher-order model (Model 2) and the bifactor model (Model 3) both fit the data equally well (see Table 1), which is not surprising given the large similarities between the modeling approaches (for parameter estimates see Figure OS 1 in online supplement). In more detail, the difference between the bifactor and the nested higher-order model was not significant, despite the large sample size ($\Delta\chi^2(9, N = 1,232) = 16.0; p = .068$). Eid, Geiser, Koch, and Heene (2016) have proposed alternative measurement models with a reference factor (or item) in case that the bifactor and hierarchical model produces anomalous results (e.g., irregular loading patterns). However, in the present case, there were no convergence problems and all nested factors had substantial factor saturation. Moreover, choosing one science subject as a reference is arbitrary and theoretically unwarranted. With respect to the parameter of interest in these models, that is, the correlation between the global science self-concept and the inferred self-concept, the different models yielded similar results. More precisely, the correlation in the higher-order factor model and the bifactor model was $\rho = .94$, which is very close to 1, although fixing the correlation to unity leads to a significant deterioration in model fit (e.g., for the bifactor model: $\Delta\chi^2(1, N = 1,232) = 11.2; p < .001$). However, given the large sample size, even very small differences are statistically significant. Moreover, constraining a correlation to the upper

boundary and testing its difference is problematic (Stoel, Garre, Dolan, & van den Wittenboer, 2006).

3.2 Gender Differences in the General Science Self-Concept

Even if the correlation between a subject-unspecific and an aggregated subject-specific science self-concept has deemed them essentially identical, this does not necessarily affect the mean structure. To examine potential differences in the factor means, we estimated a multi-group-model across gender groups with scalar measurement invariance constraints (i.e., factor loadings and intercepts; for the complete measurement invariance testing procedure of all measurement models see the supplement in the online repository:

https://osf.io/zj87n/?view_only=7dcaa15829a446428c68991e50b9b97a). In Figure 2, the mean differences across the different modeling approaches are depicted. In the four-dimensional correlated factor model, the mean-differences are rather stereotypic (Jansen et al., 2014). In the second-order model, only the means of the second-order factor can be compared to the directly measured self-concept (see also Chen, West & Sousa, 2006), because the means of the first-order factors are restricted to equality across gender groups (Chen, Sousa, & West, 2005). In contrast in the bifactor model, latent mean differences in both the general and subject-specific self-concept factors can be compared across different groups. In more detail, the gender-related mean differences are slightly more pronounced in the nested factors, while the mean difference in the general factor is surprisingly close to zero and substantially different from the separately measured science self-concept. Taken together, the factor mean differences of the different assessment approaches are not independent from the way of modeling.

3.3 Measurement Invariance Across Science Achievement

As a last point in the examination of the structural equivalence of the differently measured science self-concepts, we want to examine the invariance of the correlation depending on students' science achievement. To this end, we used the recently-proposed method of *Local Structural Equation Modeling* (LSEM, Hildebrandt et al., 2016) to study the variance-covariance structure across continuous moderators. Figure 3 shows the trajectory of the correlation across 37 equally-spaced focal points between -1.8 and 1.8 on the z -standardized scale of science achievement. At each focal point, a SEM is estimated based on a differently-weighted sample. These results should be interpreted with caution: at lower levels of the ability distribution, the robustness of the estimated SEM parameters is affected by a small effective sample size (Olaru et al., 2019). Nonetheless, the results indicate a significant drop in correlation among less-competent students. Put differently, the science self-concepts are more different in students with lower achievement scores in science. Moreover, this result is irrespective of the way of modeling.

4. Discussion

Multidimensionality and hierarchy have been postulated as the central characteristics of academic self-concepts (Shavelson et al., 1976). In the language domain, several studies examined the structure within specific language self-concepts and evaluated the assumption of multidimensionality and hierarchy (Arens & Jansen, 2016; Lau, Yeung, Jin, & Low, 1999; Yeung, Chui, Lau, McInerney, & Russell-Bowie, 2000). The results of these studies suggested both multidimensionality and hierarchy. In more detail, students possess separate self-concepts for different language aspects (e.g., reading, writing), and at the same time the language facets can be integrated into a more general self-concept that is highly similar to a directly assessed

verbal self-concept. Using a similar approach in the science domain, Hardy (2014) examined the relationship of a global, directly-assessed self-concept with a higher-order self-concept comprising of subject-specific (biology, chemistry, and physics) and interdisciplinary self-concepts (“scientific enquiry” and “nature of science”). The correlation amounted to $\rho = .87$, which was interpreted as evidence for the hierarchical nature of self-concepts in science. In line with this research, we also found a high correlation of $\rho \geq .95$ between the subject-unspecific science self-concept and an aggregated science self-concept, which can be interpreted as evidence for construct hierarchy. This seems to indicate that students implicitly “weight” their self-perceived ability in biology, chemistry, and physics when asked to assess their global science ability in the same way as the psychometric aggregation does. And this holds true irrespective of the way of modeling. In the following, we first give our take on the different psychometric modeling approaches and then argue that even such a high correlation should not be confused with the concept of equivalence in a broader sense.

4.1 Hierarchical vs. Bifactor Modeling

Reviewing the psychometric literature on hierarchical and bifactor modeling, one gets the impression that there are large statistical or conceptual differences between these modeling approaches. For example, Chen et al. (2006) listed several advantages of the bifactor model over the second-order model, but the differences are presumably more subtle (Gustafsson & Balke, 1993). Remember that the higher-order models can be turned into a special version of the bifactor models by means of the Schmid-Leiman-transformation (Reise et al., 2010, Schulze, 2004), that is, an (unconstrained) bifactor model and a higher-order model will only produce different results to the extent that the proportionality constraints are violated. In our reading, the long debate about the appropriate modeling approach is blurred by the fact that the indicators of

such models are often either parcels or subtests scores rather than items. In case of aggregated scores of different scales or subtests (e.g., Swedish and mathematics achievement as marker tests for crystallized intelligence in Gustafsson & Balke, 1993), often the bifactor model is preferred because the higher uniqueness of the indicators makes it hard to build a common trait in the higher-order model (see also Cucina & Byle, 2017). In case of parcels, the influence on modeling is more opaque (Cole, Perkins, & Zelkowitz, 2016), but parceling is often misused to mask heterogeneity by leveling out content differences (Little, Cunningham, Shahar, & Widaman, 2002), which leads to an artificial homogenization of the indicators and generally weakens the subject-specific factors.

Compared to studies discussed in the psychometric literature on hierarchical vs. bifactor modeling, there are some differences in the present case. First, all models were estimated at the item level (with rather homogeneous sets of items), making it obsolete to aggregate the responses. Second, in contrast to research on cognitive abilities that relies on high interrelations (i.e., *positive manifold*, van der Maas et al. 2006), self-concept research has to deal with two opposing self-concepts—the verbal and the mathematical self-concept that are almost unrelated (Möller, Pohlmann, Köller, & Marsh, 2009). Also, self-concepts are only moderately correlated in the sciences (Jansen et al., 2014). These differences might have led to our result of the absence of significant differences between the bifactor and the second-order model, despite the large sample size. Thus, both models concur that the aggregated science self-concept and the subject-unspecific science self-concept are very highly correlated ($\rho \geq .95$). Therefore, one might be inclined to say that both measurements are equivalent. However, in the following we point to some limitations of the statement of equivalence.

4.2 Mean Structure and Measurement Invariance

We demonstrate that in the bifactor model, the gender difference in the general factor does not match the difference in the directly measured science self-concept. In Germany, science is usually taught as separate subjects, which promotes the development of a fine-grained self-concept structure (Jansen et al., 2019). Students prompted with the task of evaluating their general science achievement without the traditional informational sources (e.g., grades) might interpolate their performance based on the perceived similarity between an existing and a hypothetical subject. In this sense, the gender difference in the directly measured, global science self-concept seems to be close to the average of the individual nested self-concepts, but not to the second-order factor. Nevertheless, bifactor modeling has the advantage that differences in the subject-specific self-concepts of the four-dimensional model are preserved. We think that valuable diagnostic information gets lost by the aggregation into a general science self-concept. To stress this point: in the debate about gender differences in STEM (*Science, Technology, Engineering, Mathematics*), the natural sciences are sometimes perceived as homogeneous group of subjects, but this is not the case. The underrepresentation of women among freshman students in Western countries refers to engineering, physical science, and computational science; there are, however, more women than men studying life sciences, such as pharmacy and biology (see also Hyde, 2014). For example, there is an overrepresentation of men receiving a bachelor's degree in physics (39.7% female) and engineering (20.4%), while the sex ratio is reversed for biomedical science (61%) and health professions (84.1%; Snyder, de Brey, & Dillow, 2019). However, enrolment rates in university courses do not depend on subject-specific achievement, but on gender, and gender-related differences in self-concept (Parker et al., 2012) and interest (Su, Rounds, & Armstrong, 2009). Since motivational factors are important predictors of

university enrolment and course selection, even after controlling for prior achievement, the subject-specific gender differences, as reported in the bifactor model, convey important information. Unfortunately, this information gets lost when self-concepts are aggregated.

Although *equivalence* is a key concept in psychological assessment (AERA, APA, & NCME, 2014) that affects score comparability and the fairness of testing, questions of measurement invariance are often neglected (see also Wicherts & Dolan, 2010). In the present study, we exemplify by means of *Local Structural Equation Modeling* that the high correlation between the differently assessed self-concepts is not static, but vary depending on science achievement. Several explanations are conceivable: it could be that less-proficient students have a lower test-taking motivation and simply work less diligently on the questionnaire. Alternatively, less-proficient students might have more difficulties to integrate the information of different subjects to infer an abstract self-concept in an area that is not directly taught. Regardless of the explanation or the magnitude of change in the specific case, we think the analyses demonstrate that differently measured self-concepts cannot be used interchangeably and questions of measurement invariance have to be taken seriously.

In conclusion, our results point in the direction of construct hierarchy of academic self-concept within the domain of science: a globally-measured science self-concept as used in international educational studies (e.g., PISA) can be considered a fairly good representation of students' general self-concept across different science subjects. Taking into account our cautionary notes on the mean structure and measurement invariance, we nonetheless recommend to assess the academic self-concept in all taught science subjects to get a more fine-grained picture.

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Model 1 Correlated-Factor Model

Model 2 Higher-Order Factor

Model 3 Bifactor Model

Figure 1. Measurement Models of General and Aggregated Subject-Specific Self-Concepts in the Natural Sciences. B = Biology, C = Chemistry, P = Physics, S = Global Science, HOS = Higher-order science factor, GS = General science factor. Please note that the residualized factor marked with a # is associated with a different interpretation of the according factor compared to the other models.

Figure 2. Gender Differences in Factor Means Across Models. Positive values indicate a higher self-concept for girls. HOS = Higher-order science factor, GS = General science factor.

Figure 3. Differentiation of Structural Equivalence of Science Self-Concepts Across Achievement. Correlation (black dots) between global and higher-order/general science self-concept across science achievement with 95% confidence intervals (dashed lines) and regression line (gray solid line). ssc = science self-concept.

Table 1

Descriptive Statistics of all Self-Concept Items

vars	Item	<i>n</i>	<i>M</i>	<i>SD</i>	Skew.	Kurtosis	Miss [%]
scb01	In biology I learn quickly.	1,224	3.69	0.97	-0.50	0.01	0.6
scb02	I have always done well in biology classes.	1,220	3.62	0.95	-0.37	-0.07	1.0
scb03	I find the subject in biology lessons easy.	1,221	3.52	0.97	-0.22	-0.32	0.9
scb04	It is easy for me to understand new ideas in biology.	1,217	3.54	0.97	-0.32	-0.20	1.2
scc01	In chemistry I learn quickly.	1,225	3.12	1.23	-0.15	-0.90	0.6
scc02	I have always done well in chemistry classes.	1,225	3.04	1.24	-0.06	-0.91	0.6
scc03	I find the subject in chemistry lessons easy.	1,224	2.95	1.22	0.03	-0.88	0.6
scc04	It is easy for me to understand new ideas in chemistry.	1,221	3.00	1.24	0.02	-0.93	0.9
scp01	In physics I learn quickly.	1,222	3.04	1.21	-0.06	-0.87	0.8
scp02	I have always done well in physic classes.	1,219	2.95	1.20	0.02	-0.80	1.1
scp03	I find the subject in physic lessons easy.	1,221	2.87	1.17	0.10	-0.75	0.9
scp04	It is easy for me to understand new ideas in physic.	1,219	2.93	1.22	0.05	-0.89	1.1
scn01	In natural science I learn quickly.	1,208	3.50	1.02	-0.36	-0.28	1.9
scn02	I have always done well in natural science classes.	1,208	3.37	1.02	-0.21	-0.35	1.9
scn03	I find the subject in natural science lessons easy.	1,203	3.23	1.00	-0.13	-0.28	2.4
scn04	It is easy for me to understand new ideas in natural science.	1,202	3.31	1.02	-0.13	-0.37	2.4

Note. Skew. = Skewness. Miss [%] = Missingness on item-level.

Table 2

Competing Measurement Models for Science Self-Concept

	Model	χ^2	df	CFI	RMSEA [90%]	SRMR	
1	Correlated factor-model	655.7	98	.961	.082	[.076; .088]	.020
1a	Correlated factor model with residual correlations	166.7	74	.994	.037	[.030; .045]	.016
2	Higher-order model with residual correlations	199.3	76	.992	.043	[.035; .050]	.031
3	Bifactor model with residual correlations	183.0	67	.992	.044	[.036; .052]	.029

Note. CFI = Comparative Fit Index; RMSEA = Root Mean Square Error of Approximation; SRMR = Standardized Root Mean Square Residual.