Rethinking the Elusive Construct of Global Self-Concept:
A Latent Composite Score as the Apex of the Shavelson Model

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This is a preprint version of a manuscript that has not been published yet (draft date: August 8, 2021). We posted all data analysis scripts on the Open Science Framework (OSF) at the following link: https://osf.io/63nk8/?view_only=0e61f97dda0b48d4bd4d10eb463a9627

Laura Braun was a doctoral student at the LEAD Graduate School & Research Network [GSC1028], which was funded within the framework of the Excellence Initiative of the German federal and state governments.

The TRAIN study was initiated and is funded by grants from the Ministries of Education, Youth, and Sports in Baden-Württemberg and Saxony, Germany. “Reanalyse und Nacherhebung der TOSCA-10-Studie [Re-analysis and post test data collection of the TOSCA-10 study]” is part of the research program “Netzwerk Bildungsforschung” (Educational Research Network) of the Baden-Württemberg Stiftung. This research project was supported by the Tübingen Postdoctoral Academy for Research on Education (PACE) at the Hector Research Institute of Education Sciences and Psychology, Tübingen; PACE is funded by the Baden-Württemberg Ministry of Science, Research and the Arts. Furthermore, this research was supported by a grant to Marion Spengler funded by the European Social Fund and the Ministry of Science, Research and the Arts of Baden-Württemberg.

We would like to thank Jürgen Baumert and Olaf Köller for granting us access to the BIJU data.

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Abstract

The multidimensional, hierarchical model of self-concept by Shavelson et al. (1976) is a cornerstone of modern self-concept research. Given the comprehensive research interest in it, it is surprising that one core aspect of this model has yet to be clarified: What is the best way to operationalize the elusive construct of global self-concept as the apex of the hierarchy? Previous research has implemented global self-concept by applying reflective modeling procedures (e.g., second-order factor models) that followed a top-down logic, which assumes that global self-concept affects lower order self-concepts. However, theoretical considerations have often equally emphasized bottom-up processes, in which lower order self-concepts form a global self-concept. Yet, a bottom-up approach has not garnered much empirical interest, most likely because the requisite statistical models have not been available. The recently proposed model-based latent composite score can fill this gap. Therefore, we contrasted top-down and bottom-up representations of global self-concept by comparing traditional one-dimensional second-order factors and model-based latent composite scores. Across three independent, large-scale studies (Study 1: $N = 8,063$; Study 2: $N = 3,081$; Study 3: $N = 2,106$), the second-order factors reproduced only small amounts of interindividual differences, which boosted the correlations with external criteria (i.e., self-esteem, enjoyment of school, academic outcomes) to theoretically and somewhat empirically implausible levels. By contrast, the composite scores showed plausible patterns of stabilities and correlations. We discuss the consequences of the two approaches and propose the latent composite score as a new perspective on the apex of the Shavelson model.

Keywords: multidimensional hierarchical self-concept, Shavelson model, global self-concept, second-order factor, model-based latent composite score

Educational Impact and Implications Statement

The present study suggests that students' various self-perceptions in different areas of life might *form* their global self-concept. By contrast, we found less support for the assumption that global self-concept *causes* how students see themselves in different areas of life. This research is important for understanding individual differences in global self-concept.

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Jasmin has a low overall opinion of herself. Likewise, she thinks she is not good at math or English and does not think she has a lot of friends. By contrast, Rafael thinks he has many friends and feels fairly positive about English; however, he thinks he is not good at math. Overall, Rafael usually thinks positive thoughts about himself. These are two examples from a large array of configurations of self-perceptions that can be found across students. These examples pose a crucial question that has drawn the interest of researchers for decades: How are students' more global and more specific self-perceptions related? For example, does Jasmin's low overall view of herself shape how she sees herself in different areas of life (e.g., in math)? Or do her perceptions of different domains (e.g., math or her social life) form her overall view of herself?

Just like Jasmin and Rafael, every student holds self-related perceptions in different areas of life and at different levels of specificity. These perceptions are typically referred to as *self-concepts*. The structure of self-concepts has been studied intensively across the last several decades of educational research. In this context, the *Shavelson model* (Marsh, 1987; Marsh & Shavelson, 1985; Shavelson et al., 1976) has become the most influential model (cited 5,680 times on Google Scholar in early 2020). Along with describing self-concept as structured, stable, developmental, evaluative and differentiable, the Shavelson model defines self-concept as a multidimensional (i.e., including self-concepts in domains such as math, English, or social contexts) and hierarchically ordered (i.e., more global and broader self-concepts are located at higher levels of the hierarchy) construct. There is comprehensive and convincing evidence for the multidimensionality of self-concept (Brunner et al., 2010; Marsh, 1986b, 1987, 1990; Marsh & Shavelson, 1985; Shavelson & Marsh, 1986), yet its hierarchical nature has puzzled researchers to this day. This is likely the case because an explicit, substantive definition of global self-

concept was missing from the Shavelson et al. (1976) article. Another major reason for this might be that the theoretical considerations of the direction underlying the hierarchy of self-concept postulated by Shavelson et al. (1976) sometimes appeared to contradict each other. Therefore, whether and how they match up with the subsequent methodological implementations is an open question, yet such a match would be an important requirement for drawing valid conclusions (Greenwald, 2012; Marsh & Hau, 2007). As a consequence, it is still unclear whether global self-concept is conceptualized as being formed by more specific self-concepts in a bottom-up way or whether global self-concept is conceptualized as a higher order construct that affects more specific self-concepts in a top-down manner. A better understanding of global self-concept is important (a) because of its centrality in this influential model, (b) for identifying and better understanding the emergence and long-term effects of global self-perceptions, and (c) for the potential to make decisions about starting points from which to successfully foster global self-concept.

Besides a lack of clarity regarding the definition of global self-concept, methodological restrictions have limited researchers to using top-down concepts of global self-concept. Thus, widely available higher order factor models, which follow a top-down logic, have dominated the analyses of the Shavelson model (Shavelson et al., 1976) and its extensions (Arens et al., 2020; Brunner et al., 2010; Marsh, 1986b, 1987, 1990; Marsh & Shavelson, 1985; Shavelson & Marsh, 1986). Until recently, alternative models that allow researchers to test the theoretical idea of bottom-up processes and can account for measurement error have not been available to applied researchers. Using newly developed latent variable models for latent composite scores (Rose et al., 2019), we examined a bottom-up representation of global self-concept. We compared this

new approach with traditional one-dimensional second-order factor models¹ (see, e.g., Marsh & Hocevar, 1985) using three independent, large-scale studies (Study 1: $N = 8,063$; Study 2: $N = 3,081$; Study 3: $N = 2,106$) that contained different sets of self-concept measures. To evaluate the consequences and implications of the two approaches, we targeted different internal criteria (i.e., intercorrelations between self-concept measures, descriptives, and stabilities of global self-concept) as well as external criteria (i.e., correlations with different external criteria).

Second-Order Factor Operationalizations of Global Self-Concept

According to Marsh and Craven (1997) and extended by Brunner et al. (2010), there have been different evolutionary phases in research on the structure of self-concept, and they have made different assumptions about global self-concept. Until the 1970s, self-concept research appeared to be in a so-called *Dustbowl Phase* (Marsh & Craven, 1997) in which researchers used multiple self-concept items and summed them to obtain a global self-concept score. However, the composition and inclusion criteria for the self-concept items (e.g., Coopersmith, 1967; Fitts, 1965) lacked a solid theoretical and empirical foundation, and the methodological approaches reflected contemporary standards in that researchers did not account for measurement error or missing data.

To overcome the previous (theoretical) limitations of self-concept research, Shavelson et al. (1976) proposed a multidimensional (e.g., math, verbal, social) and hierarchically ordered model of self-concept, which is commonly referred to as the *Shavelson model*. In this model, global (or general) self-concept is located at the apex of the hierarchy with academic and nonacademic self-concept at the intermediate level and self-concepts in different subdomains

¹ It is important to note that we contrast this new approach only with traditional one-dimensional second-order factor models, and not to reflective approaches which require an additional direct measurement of global (academic) self-concept (see Brunner et al., 2010). When interested in a certain (second-order) construct, it may be advantageous to measure it directly through multiple indicators, instead of deriving it statistically.

(e.g., math or physical appearance) at the lowest level, which we will refer to as lower order self-concepts. However, the Shavelson et al. (1976) article allowed for some leeway in how the hierarchy could be interpreted. On the one hand, they posited that changes in higher order self-concepts require preceding changes in lower order self-concepts (“To change general self-concept, many situation-specific instances, inconsistent with general self-concept, would be required”; Shavelson et al., 1976, p. 412). The assumed directional influence of lower order self-concept on higher order self-concept may be interpreted as a bottom-up process of formation within the hierarchy of self-concept. On the other hand, they described attenuation processes from higher order factors (“Furthermore, changes at the lower levels of the hierarchy are probably attenuated by conceptualizations at higher levels, making self-concept resistant to change”; Shavelson et al., 1976, p. 412) and compared the hierarchy of self-concept with the g-factor approach from the hierarchical structure of intellectual abilities (see, e.g., Spearman’s g-factor; Soares & Soares, 1977; Vernon, 1950). The latter consideration was implemented via confirmatory factor analysis, which assumes a reflective latent variable model that, if interpreted in a realistic manner, explicitly implies a top-down process (Borsboom et al., 2003). These conflicting assumptions about the nature of global self-concept line up with different theoretical views from other streams in this field of research. Whereas bottom-up ideas were already described by James (1890/1963), who believed that global self-views were shaped by the appraisal of multiple characteristics and abilities, Brown (1993) emphasized the top-down idea by stating that global self-perceptions are formed at very early ages and serve as an adaptive resource that helps people interpret and know how to act in life. Despite these contradictory assumptions about both bottom-up and top-down ideas within the hierarchy of self-concept, Marsh and Shavelson (1985) almost exclusively jumped on the confirmatory factor analysis bandwagon to implement global self-concept, which follows the top-down approach. This

methodological operationalization was a path-breaking decision as it has dominated research on self-concept to this day.

However, the first studies to use (one-dimensional) second-order confirmatory factor analysis (see Figure 1, Part a) had already encountered difficulties because second-order factor models did not fit the data well, and global self-concept (represented as the second-order factor) tended to have a small variance, which resulted from low correlations between math and verbal academic self-concepts (Brunner et al., 2008; Marsh, 1986b, 1987, 1990; Marsh & Hau, 2004; Marsh & Hocevar, 1985; Marsh & Shavelson, 1985; Shavelson & Marsh, 1986). These low correlations even decreased with age (Marsh, 1989; Marsh et al., 1991; Marsh & Ayotte, 2003). Notwithstanding the empirical problems of (one-dimensional) second-order factor models (i.e., a small variance based on low correlations between academic self-concepts), its results have been widely interpreted. For example, a second-order factor for global self-concept and unidimensional global self-esteem were highly correlated, which led researchers to conclude that they probably represented the same construct (Marsh & Hattie, 1996). However, this conclusion was made without acknowledging potential problematic parameter estimates due to the small variances of the second-order factor.

At the same time, Marsh and Shavelson (1985) called the existence of global self-concept into question more generally. On the basis of the low correlations, they proposed that academic self-concept be separated into two distinct factors representing math and verbal academic self-concept (see Figure 1, Part b), and they consequently abandoned global (academic) self-concept. This model is known as the *Marsh/Shavelson model* (Marsh, 1990). Driven both by theoretical considerations (i.e., accounting for the multidimensionality and hierarchy of self-concept; see Arens et al., 2020) and further methodological developments in confirmatory factor analysis (Eid et al., 2003), Brunner and colleagues postulated the *Nested Marsh/Shavelson model* for academic

self-concepts but not for global self-concept (see Figure 1, Part c). This model separates general academic self-concept from domain-specific (method) factors using a correlated trait correlated method minus one (CT-C[M-1]) approach (Brunner et al., 2008; Brunner et al., 2009; Brunner et al., 2010; Eid et al., 2003). The Nested Marsh/Shavelson model fit the self-concept data better than previous versions (Brunner et al., 2008; Brunner et al., 2009; Brunner et al., 2010). In line with the second-order factor model, this approach follows a reflective modeling approach. Yet, in contrast to the second-order factor model, it does not pose a clear hierarchical ordering between lower and higher order academic self-concepts. Instead, this model includes a direct measure of global academic self-concept, which leads to a different interpretation of higher and lower order factors.

In sum, the Shavelson model stimulated important developments in research on the structure of self-concept. Theoretically, in several parts of their article, Shavelson et al. (1976) proposed a bottom-up approach within the hierarchy of self-concept, yet at the same time, they made conflicting arguments when drawing on attenuation processes and on the g-factor analogy, which underlies a top-down approach. Along with elaborated methodological work, such as (second-order) confirmatory factor analysis, this led to a number of important developments that were identified as important “evolutionary steps[s]” in the modeling of self-concept (Brunner et al., 2010, p. 976). However, from a perspective that emphasizes bottom-up processes, these elaborated top-down models might instead represent only one of several possible developments and might thereby actually hamper possible developments. In fact, considerations of the differences and consequences of top-down *and* bottom-up approaches for representing the structure of self-concept now call for a deeper understanding of their empirical implementations (Bollen & Diamantopoulos, 2017; see, e.g., Bollen & Lennox, 1991; Edwards & Bagozzi, 2000; MacKenzie et al., 2005).

Assumptions of Reflective and Formative Modeling Approaches

When choosing the most appropriate statistical (measurement) models, it is of central importance to achieve a good match with the assumed theoretical ontology of a construct (Borsboom et al., 2003, 2004). In the following, we therefore reviewed the statistical assumptions of the two modeling approaches representing a top-down versus a bottom-up implementation of the hierarchy of self-concept. In doing so, (a) we focused on the second-order level, which represents the structural relations between lower order self-concepts and global self-concept, and not on the lowest level (i.e., the relations between item indicators in terms of measurement²), and (b) we addressed the directional link within the self-concept hierarchy by deriving global self-concept from a statistical model (i.e., not measuring it directly) with either an underlying top-down (i.e., higher order factor) or bottom-up (i.e., composite score) mechanism. We did not address top-down versus bottom-up ideas by making temporal predictions between different hierarchically ordered self-concepts over time (e.g., testing whether directly measured global self-concept prospectively predicts lower order self-concepts [i.e., also considered top-down] or is predicted by lower order self-concepts [i.e., also considered bottom-up]; for this approach, see Harris et al., 2018; Marsh & O'Mara, 2008; Marsh & Yeung, 1998; Rentzsch & Schröder-Abé, 2018; Trautwein et al., 2006).

Reflective models are the most commonly used measurement models in psychological research (Borsboom et al., 2003). In reflective models, higher order constructs are causes of indicators (in our case, lower order self-concepts), often referred to as effect indicators (Blalock, 1964). These models presume a causal relation from a higher order (inferred) construct to its

² The focus of the first level is the measurement of the respective domain-specific self-concepts. More specifically, the underlying (domain specific) self-concepts are responsible for the response each student provides on the item indicators. Reflective approaches are designed to address the problem of measurement error. The second level, however, is concerned with the structural relation of the first-order factors and the second-order factor. At this level we contrast the top-down vs. bottom-up approaches.

indicator in such a way that a change in the (higher order) construct determines a change in the indicators (Edwards & Bagozzi, 2000). In general, the higher order construct is modeled to represent a unidimensional construct, which calls for moderate to high positive intercorrelations between its indicators and assumes that the indicators should be interchangeable (Bollen & Lennox, 1991). Analyses of traditional one-dimensional second-order reflective models representing global self-concept have run into difficulties, most likely because of the low correlations between the lower order self-concepts that have been in conflict with the assumptions of reflective models (Bollen & Lennox, 1991). This makes a reflective model questionable because—by definition—it can explain only a small proportion of common variance in the lower order constructs. Indeed, Marsh (1987) already noted that previous results on the hierarchy of self-concepts

“ [...] have more negative consequences for a top-down model that makes the stronger theoretical assumption that the hierarchical general self "causes" the lower order facets. If a hierarchical general self is posited to cause a lower order factor but the two are nearly uncorrelated, then the postulated causal relation is not supported.” (Marsh, 1987, p.34)

As a consequence, on the basis of a systematic and rigorous application of state-of-the-art methodology, previous self-concept research has concluded that the top-down order must be “more complex” (Marsh & Shavelson, 1985, p. 121). However, what was missing back then were alternative statistical models that would have allowed for a sophisticated formative bottom-up modeling of global self-concept.

A Latent Composite Score Model: A New Evolutionary Pathway

In fact, the causal flow of formative modeling approaches is the opposite of reflective models. Here, indicators form higher order constructs (Bollen & Lennox, 1991; Edwards & Bagozzi, 2000) and are therefore called cause, causal, formative, or composite indicators

(Blalock, 1964; Bollen & Lennox, 1991). Accordingly, the higher order construct is formed by the indicators. This requires that all indicators that form the construct are included in the model (Bollen & Lennox, 1991). In contrast to reflective models, removing an indicator has an impact on the nature of the construct. Furthermore, formative models do not require high intercorrelations between the indicators. The variance of the higher order construct is based on the conglomerate of the variances of the indicators.

So far, there has been little research on a formative perspective on the hierarchy of self-concept. The few existing studies go back to the time before the Shavelson model was introduced (e.g., Coopersmith, 1967; Hishiki, 1969; Ludwig & Maehr, 1967; Sears et al., 1972; Soares & Soares, 1969; Zirkel, 1971). At that point, global and domain-specific self-concept were modeled using the simple sum of a series of self-concept items that addressed self-concept in different areas of life. However, these studies lacked a clear theoretical and methodological foundation.

Historically, formative approaches have been criticized because of the difficulty of identifying the models (i.e., because they require a predicted variable) and because they ignore measurement error (Bollen & Diamantopoulos, 2017), which has dramatic consequences for results in psychological research (e.g., Cole & Preacher, 2014). Correspondingly, this led to a boost in reflective (measurement) models across psychology and beyond. These models were relatively easy to implement and accounted for measurement error in the observed variables (Borsboom, 2008; Rhemtulla et al., 2019). However, more recent methodological considerations have emphasized that model choice should not be driven by the ability to handle measurement error but by the theoretical ontology of a psychological construct (Rhemtulla et al., 2015, 2019). The misplaced application of reflective (measurement) models can result in the invalidity of the construct, model misfit, and biased structural estimates (Rhemtulla et al., 2019). Moreover, Rose et al. (2019) developed a formative approach for obtaining latent composite scores that are free

from measurement error and can be implemented easily³. The central idea guiding this research was to examine both a top-down approach by using reflective models and a bottom-up approach by using a formative model to construe a global self-concept factor.

The Present Study

In the present research, we aimed to examine an alternative approach (i.e., bottom-up formation process) to operationalize the elusive construct of global self-concept as the apex of the self-concept hierarchy. Thus, we asked the question of whether global self-concept is formed by different lower order self-concepts or whether it is the cause of different lower order self-concepts. In the present study, we addressed this question by comparing the consequences of a top-down versus a bottom-up representation of global self-concept as the apex of the Shavelson model (Shavelson et al., 1976). In empirical studies, the Shavelson model was nearly exclusively considered a top-down model because it was based on reflective modeling procedures. In addition, previous results on the Shavelson model when reflective models (i.e., the traditional one-dimensional second-order factor models) were used revealed difficulties because the lower order self-concept factors were barely correlated, which contradicted the crucial assumption of a common underlying cause in reflective models. In the present exploratory research, we provide insights into the consequences of a bottom-up representation of the Shavelson model using a formative modeling procedure. To do this, we analyzed three independent longitudinal large-scale studies that included different sets of self-concepts and compared the consequences of the reflective and formative representations of the Shavelson model by drawing on the internal (i.e.,

³ In previous literature, the term *formative* has been used to refer to different modeling procedures Bollen and Bauldry (2011). Whereas some researchers have used the term *formative indicators* to refer to composite indicators, others have used it to refer to causal-formative indicators that include an outcome variable as well as a disturbance term. In the present study, we use the term composite indicators and refer to them as part of the conceptual idea of formative models. Therefore, we do not further distinguish between the terms composite and formative indicators (or composite and formative models, respectively). In addition, we focus on the formative second-order level and not on the formative first-order level see, e.g., Diamantopoulos et al. (2008).

properties within the model) and external (i.e., relations to other constructs) criteria of the models.

Internal criteria. For the internal criteria, we addressed three overarching research questions. First, we analyzed the intercorrelations between the lower order self-concepts (Research Question 1). This pattern of intercorrelations is particularly interesting because it lays the foundation for further modeling decisions (e.g., Bollen & Lennox, 1991). We expected to replicate the findings of previous studies that showed that (at least some of the) first-order self-concepts are barely correlated (Marsh & Shavelson, 1985). Second, when analyzing reflective and formative models, we descriptively examined how the models reproduced interindividual differences in terms of the variances of global (academic) self-concept. Because we cannot directly compare the sizes of the variances from the reflective and the formative model, we additionally used the average amount of variance explained in the first-order factors of the reflective model (i.e., of the second-order factors) as an indicator of how much variance global (academic) self-concept can depict (Research Question 2). Third, we analyzed whether the temporal stabilities of global (academic) self-concept differed between the reflective and formative approaches (Research Question 3). Shavelson et al. (1976) considered the stability of different hierarchical elements to be one important feature of his model and assumed that global self-concept should be very stable over time.

External criteria. Along with these internal criteria, we analyzed the relation between global (academic) self-concept and external criteria in order to gain a broader understanding of the consequences of the two approaches. In the convergent validity framework (Campbell & Fiske, 1959), we asked how global self-concept (operationalized by the two approaches) is related to theoretically similar constructs (Research Question 4). We chose different target constructs: Primarily, we expected that global self-concept would be positively related to global

self-esteem (Marsh & Shavelson, 1985), which was directly measured with standard questionnaires (Study 1: Rosenberg Self-Esteem Scale, Rosenberg, 1965; Study 2: Self-esteem scale from the children's quality of life scale [KINDL], Ravens-Sieberer et al., 2001). Self-esteem typically refers to a unidimensional construct that is defined as the global, subjective evaluation of one's own worth (Donnellan et al., 2011). In previous studies, global measures of self-esteem and an inferred second-order factor based on different self-concept measures were highly correlated (Marsh & Hattie, 1996). Yet it is unclear what caused these high correlations given the small variances of the second-order factor models. Second, we analyzed the relation between global (academic) self-concept and students' enjoyment of school (Study 1), which is supposed to be an important outcome of students' adjustment and is a construct that was previously used to evaluate the construct validity of self-concept measures (Marsh & O'Neill, 1984). Finally, we analyzed the relations between global academic self-concept and global academic outcomes. Previous research had shown that self-concepts are reciprocally related to academic outcomes in the same domain (Marsh & O'Neill, 1984; Marsh & Yeung, 1998). Following the matching specificity principle (Swann et al., 2007), we identified outcomes that were on a comparable specificity level as global self-concept. Therefore, we chose to analyze very global academic outcomes, such as an average achievement score, grade point average, and the transition after secondary school.

In order to empirically model the reflective approach, we used traditional one-dimensional second-order factor models. For the formative approach, we used a newly developed modeling procedure, namely, the model-based-latent composite score (Rose et al., 2019). The main advantages of this approach compared with classical formative models are that (a) it can model composites of first-order factors, which are free from measurement error, (b) missing data can be considered by means of full information maximum likelihood estimation, (c) it allows the

implementation of a formative composite variable independent of outcome-dependent weights, and (d) it can be implemented easily in conventional statistical software for structural equation models (e.g., Mplus or R; see Rose et al., 2019).

Method

The data sets used in the present study came from three multiconstruct large-scale studies. The data were collected in adherence with ethical principles in the treatment of sensitive personal data and were approved by the responsible school authorities (Study 1) and by the ministries of education and cultural affairs of the German states of Saxony (Study 2) and Baden-Württemberg (Studies 2 and 3).

Samples and Instruments

Study 1: BIJU. We analyzed data from the German multicohort longitudinal study “Learning Processes, Educational Careers and Psychosocial Development in Adolescence and Young Adulthood” (BIJU; Baumert et al., 1996). We used data from students in the first cohort at the beginning and end of Grade 7 (T1: $N = 5,948$; T2: $N = 6,263$) from academic and nonacademic schools in four German federal states (North Rhine-Westphalia, Saxony-Anhalt, Mecklenburg Western Pomerania, and Berlin [Berlin participated only at T2]). The total sample included $N = 8,063$ students (53% female), who participated at a minimum of one time point. The study incorporated the assessment of eight self-concepts, including five academic (Jerusalem, 1984; Jopt, 1978) and three nonacademic self-concepts (Fend & Prieser, 1986). In Table 1, the self-concept measures and their internal consistencies are displayed in detail. In sum, the self-concept measures consisted of three to four items and showed good reliabilities ($\alpha > .70$)⁴. Self-

⁴ The social self-concept and the self-concept of appearance measures in the BIJU study and the German self-concept measure in the TRAIN study produced low (standardized) factor loadings ($< .30$) for three items. We reran the final models without these items. The results were virtually unchanged. To ensure the content validity of the constructs, we kept the items in the analyses.

esteem was measured with a four-item German version (Jerusalem, 1984; Trautwein, 2003) of the Rosenberg Self-Esteem Scale (Rosenberg, 1965). Previous analyses showed that the short and the long versions of the Rosenberg scale were strongly correlated (Trautwein, 2003). The self-esteem scale showed good reliabilities ($\alpha > .75$). Furthermore, enjoyment of school was measured with three items ($\alpha > .65$) that assessed the overall pleasure and enjoyment of school (e.g., “I like going to school”). All items were rated on a 4-point Likert scale ranging from 1 (*totally disagree*) to 4 (*totally agree*).

Study 2: TRAIN. We analyzed data from the German longitudinal school achievement study “Tradition and Innovation” (TRAIN; Jonkmann et al., 2013). In total, we considered data from $N = 3,081$ students (45% female) in Grade 5 ($T1 = 2,101$) and Grade 8 ($T2 = 2,382$) from 136 classes in 99 nonacademic schools in two federal German states (Baden-Württemberg, Saxony). In the TRAIN study, five self-concepts were assessed at both time points, including three academic self-concepts (math, German, English) and two nonacademic self-concepts (social, assertiveness). Table 1 presents an overview of the measures and their internal consistencies. In sum, the measures contained three to four items and showed good reliabilities ($\alpha > .66$). All self-concept measures were rated on a 4-point Likert scale ranging from 1 (*totally disagree*) to 4 (*totally agree*). Self-esteem was measured with the four-item self-esteem scale from the KINDL-R scale (Ravens-Sieberer et al., 2001), which assessed students’ self-esteem (e.g., “In the last week, I was proud of myself) using a 5-point Likert scale ranging from 1 (*never*) to 5 (*always*) and showed good reliabilities ($\alpha > .71$).

Study 3: TOSCA-10. We employed data from the German longitudinal study “Transformation of the Secondary School System and Academic Careers: Grade 10” (TOSCA-10; Trautwein et al., 2011). The study was designed to investigate the transition of nonacademic intermediate 10th grade students to further education. At the first time point in Grade 10, data

from $N = 2,106$ students (51% female) were assessed. At the second time point, $N = 473$ students could be assessed again, which took place 6 years later in order to assess students' educational trajectories. The study included five academic self-concepts (math, verbal, English, economic, technical) with four to eight items each that were rated on a 4-point Likert scale ranging from 1 (*totally disagree*) to 4 (*totally agree*) and showed good reliabilities ($\alpha > .76$; for details, see Table 1). Additionally, grade point average and an average standardized achievement score (German, English, math, biology, economics, technology) in Grade 10 and the educational trajectories 7 years later were assessed. Thereof, we used an indicator of whether students chose the academic ($N = 188$) or vocational track ($N = 285$) after Grade 10.

In all three studies, we drew on all domain-specific self-concept measures that were available in the data sets from the two waves of assessment used in the present study (there was one exception: Studies 1 and 2 included a measure of the self-concept of intelligence. However, we view this measure as existing on a different hierarchical level than the other self-concept measures, and we do not necessarily see the self-concept of intelligence as a domain-specific self-concept).

Statistical Analyses

Second-order factor model (SOF). For the reflective approach, we used traditional one-dimensional second-order factor models (see the lower left part of Figure 2). First, $\eta_1 \dots \eta_Q$ first-order factors were modeled for all self-concept measures. Second, a second-order factor ξ was modeled in order to explain the covariation between the first-order factors. All first-order factors (from both the second-order factor model and the composite score model) as well as the second-order factor were identified by a “nonarbitrary” model identification (Little et al., 2006). This identification approach applies a weighted combination of all indicators to ensure an optimal

balance across indicators. Thus, through an average intercept of zero and an average factor loading of 1, the latent variable obtains an optimally weighted metric across all indicators.

Model-based latent composite score (LCS). For the formative approach, we used model-based latent composite scores (see the lower left part of Figure 3). The LCS is a model that was recently developed by Rose et al. (2019). It allows composite scores to be estimated on the basis of first-order factors that account for measurement error. We chose to model an *average* composite score (for a sum score, see Rose et al., 2019). The model is similar to a latent change score model, except that an average instead of a difference is modeled. First, $\eta_1 \dots \eta_Q$ first-order factors are modeled for all components of the composite score (all self-concept measures). In line with the second-order factor model, they were identified by a nonarbitrary model identification. In the next step, one of the first-order factors was arbitrarily chosen as the pseudo-indicator variable η_{PIM} , which was modeled as the indicator of the composite score with a factor loading of the number of first-order factors and a fixed residual of 0. The paths of the other $\eta_1 \dots \eta_{Q-1}$ first-order factors on the pseudo-indicator variable η_{PIM} were fixed to -1. Doing this ensured that all components (i.e., domain-specific self-concepts) were equally weighted in the composite score, which is a relatively strong assumption (see below for a more detailed discussion). Currently, weights cannot be estimated empirically in the LCS approach. Rather, they have to be assigned theoretically before the analyses are run (for a weighted composite score, see Rose et al., 2019). Because this is the first application of the LCS model to self-concept measures, we weighted all domain-specific self-concepts equally. The latent LCS incorporates full information maximum likelihood estimation in order to adjust for item nonresponses and missing data in manifest variables.

Analytical procedure. In order to analyze the consequences of using a reflective versus a formative approach to assess the hierarchy of self-concept, we drew on the internal and external

criteria from the modeling approaches used in three different longitudinal studies. In a first step, we analyzed the latent correlations between the lower order self-concepts. Second, we modeled global (academic) self-concept⁵ separately by applying the SOF and the LCS by using a stepwise inclusion of the self-concept measures and by computing its descriptives, its stabilities, and its relations to external criteria (see Figures 2 and 3). All models included both time points with strong measurement invariance imposed across time in the measurement models (Meredith, 1993). In addition, in the second-order factor model, we assumed strong measurement invariance across time in the structural model (i.e., loadings and intercepts of the first-order factors). We addressed three aspects of second-order factor and composite score models, which are displayed in bold lines in Figures 2 and 3. First, we investigated the variances of global self-concept ($\hat{\sigma}^2_{\text{GSC}}$). Second, we investigated the temporal stability, which is represented by the correlation coefficients between the measurement time points across 1 (Study 1), 4 (Study 2), and 7 (Study 3) years ($r_{\text{GSC T1, GSC T2}}$). Third, we analyzed external relations by computing the correlations of global self-concept with global self-esteem and enjoyment of school (Studies 1 and 2) and global academic outcomes (Study 3), that is, average achievement, grade point average, and the transition after Grade 10 ($r_{\text{GSC, Outcome}}$). In addition to the correlations, we present the covariances of the parameters because the correlations are directly influenced by the variances of the constructs (i.e., a correlation is equal to the covariance rescaled by the variances). Thus, the same covariance can turn into largely different correlations given the variances of the constructs.

⁵ Due to the differences in the inclusion of different domain-specific self-concepts, in Studies 1 and 2, we use the term global self-concept, whereas in Study 3, we use the term global academic self-concept. Whenever we speak of the results across the three studies, we use the term global (academic) self-concept. More generally, the definition of the composite score is fundamentally determined by the selection of domain-specific self-concepts.

All models were estimated in Mplus 8.2 (Muthén & Muthén, 1998-2017). All data analysis scripts are available for review on the Open Science Framework at the following address: https://osf.io/63nk8/?view_only=0e61f97dda0b48d4bd4d10eb463a9627 (the project will be publicly available after the review process has been completed). Due to specific item variance, we a priori allowed for correlated uniquenesses of (a) the same items over time and (b) reversed item formulations. After seeing the initial model fit, we also allowed for correlated uniqueness (c) across self-concept items with the same wording (Cole et al., 2007; Marsh & Hau, 1996; Nagengast et al., 2013). Due to missing values on single items and over time, we used full-information maximum likelihood estimation (FIML). In order to rule out the possibility that different sets of missing data were responsible for differences between particular models, we included the same set of variables in all models. Thus, the FIML estimation was held constant across all models, and the models differed only in the specification of the structural model (i.e., which self-concepts were included in the second-order factor/composite score) but not concerning the measurement models and the covariances with the outcome variables. We took the nested data structure into consideration (i.e., students nested within classes) by using cluster-robust standard errors (McNeish et al., 2017; Muthen & Satorra, 1995). Across all three studies, longitudinal measurement models including all correlated first-order self-concepts fit the data well (CFI > .939, TLI > .922, RMSEA < .037; SRMR < .048; see the Appendix). The specification of the model-based LCS did not affect the model fit as there were no additional implications regarding the means or the covariance structure on other variables in the model. Hence, the model with the LCS always had the same degrees of freedom and the same fit as the model with correlated first-order factors (Rose et al., 2019). The longitudinal second-order factor models showed mostly acceptable model fits across all three studies (CFI > .921, TLI > .903, RMSEA < .042, SRMR < .122; see the Appendix). There were some warnings during model

estimation (predominantly for the SOF models). The warnings mainly resulted from nonpositive definite matrices (e.g., latent covariance matrix or first-order derivative product matrix) and most likely occurred because there were more parameters than there were clusters, a latent variable had a negative (residual) variance, or there was a correlation greater than or equal to 1. The fits of all the models, including the models with external criteria, as well as an overview of the warnings are presented in the Appendix (see Tables A1, A2, and A3).

Results

Internal Criteria

Before investigating global self-concept, we began by analyzing the latent correlations between the lower order self-concepts in the three studies (Research Question 1). Tables 2, 3, and 4 depict the intercorrelations between the lower order self-concepts in the three studies at two time points each. The results indicated that, across all three studies, most of the correlations were low to medium⁶ ($r < .30$) and positive. However, correlations among conceptually distinct domains (e.g., math and verbal) were close to zero or even negative. In addition, some correlations among conceptually similar domains (e.g., English with verbal; social with appearance) were rather high ($r > .30$). Correlations between the same lower order self-concept over time (i.e., rank-order stabilities) were also rather high (Study 1: $r = .39$ to $.59$; Study 2: $r = .34$ to $.50$; Study 3: $r = .47$ to $.79$).

In the next step, we specified second-order factor (SOF) and latent composite score (LCS) models that represented global self-concept. To be more specific, we examined different numbers and combinations of lower order self-concepts in order to gain an understanding of the dependencies and sensitivities in the two modeling approaches. First, we were interested in the

⁶ The size of the correlations are evaluated based on the guidelines of Gignac and Szodorai (2016). We thank the reviewer of referring us to these guidelines.

variances (i.e., interindividual differences) of the respective global self-concepts (Research Question 2). As indicated in Table 5, across all three samples, all sets of self-concepts, and all time points, the composite scores exhibited variances in the range of $\hat{\sigma}^2_{LCS} = 0.10$ to 0.33 . By contrast, the variances of the second-order factors were in the range of $\hat{\sigma}^2_{SOF} = -0.12$ to 0.26 , and, thus, even yielded negative estimates. More specifically, in Studies 1 and 2, the variance of the second-order factor was particularly small when only academic self-concepts were included ($\hat{\sigma}^2_{SOF} = 0.06$ to 0.13) compared with when only nonacademic self-concepts were included ($\hat{\sigma}^2_{SOF} = 0.14$ to 0.26). In Study 3, which included only academic self-concepts, the variance of a second-order factor based on only two self-concepts yielded a negative variance ($\hat{\sigma}^2_{SOF} = -0.12$), and the second-order factor model based on three self-concepts did not converge. As an even more important indicator of the variance in the second-order factor, we also looked at the average amount of variance explained in the first-order factors. Across the three studies, the average amount of explained variance was mostly low when academic self-concepts were included (Study 1: $R^2 = .19$ to $.33$; Study 2: $R^2 = .22$ to $.38$; Study 3: $R^2 = .01$ to $.04$), whereas it was much larger when only nonacademic self-concepts were included (Study 1: $R^2 = .62$ to $.77$; Study 2: $R^2 = .54$ to $.66$). Not surprisingly, the means of the second-order factor and the composite score did not differ substantially because the first-order factors were identified by the same identification method.

After examining the variances, we were interested in the stabilities of global self-concept modeled by a second-order factor and a composite score (Research Question 3). We examined the temporal stabilities from the three studies across 1 (Study 1), 4 (Study 2), and 7 years (Study 3). Tables 6 and 7 depict the covariances and correlations between the respective time points in the three studies with a stepwise inclusion of self-concepts. Across the three studies and across all sets of self-concepts, the covariances were typically higher for the composite score than for the

second-order factor. However, the correlations were almost always higher in the second-order factor, which is most likely a result of the small(er) variances in the second-order factor that boost up the correlations. The differences between the two approaches were small in Study 1 ($r_{\text{SOF}} = .50$ to $.70$; $r_{\text{LCS}} = .50$ to $.59$) and more pronounced in Study 2 ($r_{\text{SOF}} = .50$ to $.75$; $r_{\text{LCS}} = .39$ to $.49$) and Study 3 ($r_{\text{SOF}} = .91$; $r_{\text{LCS}} = .64$ to $.68$). In addition, in Study 3, it was not possible to estimate the correlations of the second-order factor when two or three self-concepts were included due to the negative variances in the second-order factor or nonconvergence (see Table 5). Across Studies 1 and 2, the correlations across the different sets of self-concept were more similar (i.e., they had a smaller range) in the composite score than in the second-order factor.

In sum, we observed mostly low (to medium) correlations between the lower order self-concepts, which transferred into small variances of the second-order factor (see Table 5). These small variances most likely inflated some of the stabilities in the second-order factor (see Tables 6 and 7). By contrast, the variances of the composite scores were higher and their stabilities were more consistent, given different sets of lower order self-concepts.

External Criteria

As the second major step in our analyses, we were interested in the relations between global self-concept, modeled with the two approaches, with external criteria (Research Question 4). For Studies 1 and 2, we looked at global self-concept's relations to global self-esteem and enjoyment of school. In Study 3, which included only academic self-concepts, we looked at global self-concept's relations to global academic outcomes, namely, an average achievement score, grade point average, and the transition after Grade 10 (academic vs. vocational track).

Table 6 presents the covariances and correlations of global self-concept with global self-esteem and enjoyment of school in Studies 1 and 2. Regarding the relations between global self-concept and self-esteem, across both studies and in all sets of self-concepts, the covariances were

very similar in the second-order factor and the composite score. By contrast, the correlations were consistently higher in the second-order factor (Study 1: $r_{\text{SOF}} = .52$ to 1.03 ; Study 2: $r_{\text{SOF}} = .41$ to $.64$) than in the composite score (Study 1: $r_{\text{LCS}} = .42$ to $.91$; Study 2: $r_{\text{LCS}} = .35$ to $.48$). Across both studies and both time points, reducing the number of self-concepts to model a second-order factor was typically associated with increases in the correlation with self-esteem, whereas this was not the case in the composite score model. For example, the correlations between the second-order factor and global self-esteem were among the highest when only two academic self-concepts were included (Study 1: $r_{\text{SOF}} > .74$; Study 2: $r_{\text{SOF}} > .61$). In Study 1, some correlations from the second-order factor were implausibly high ($r_{\text{SOF}} > 1$).

The covariances and correlations with regard to the second external criterion (i.e., enjoyment of school) in Studies 1 and 2 are also presented in Table 6. Paralleling the findings for self-esteem, the covariances between global self-concept and enjoyment of school were very similar in the second-order factor and the composite score. In line with the findings on self-esteem, most of the correlations were higher in the second-order factor than in the composite score. Across the two studies, the range of the correlations with varying self-concepts was smaller among the correlations from the composite score (Study 1: $r_{\text{LCS}} = .18$ to $.36$; Study 2: $r_{\text{LCS}} = .15$ to $.46$) than among the ones from the second-order factor (Study 1: $r_{\text{SOF}} = .20$ to $.52$; Study 2: $r_{\text{SOF}} = .19$ to $.79$). In the second-order factor, the correlations were highest when only two or three academic self-concepts were included. Across both studies and both modeling approaches, the correlations between global self-concept and enjoyment of school were higher when global self-concept was based on academic rather than nonacademic self-concepts.

As indicated in Table 7, in Study 3, results on the relations between global self-concept and three academic outcomes (average achievement score, grade point average, decision about the transition) indicated that the covariances and correlations were higher for the composite score

($r_{LCS} = .10$ to $.52$) than for the second-order factor ($r_{SOF} = .10$ to $.40$). In the second-order factor, it was not possible to estimate the correlations between global self-concept and the academic outcomes when two or three self-concepts were included. Again, this was due to the negative variance of global self-concept in one model and the nonconvergence in the other model (see Table 5).

Overall, the relations to external criteria (i.e., self-esteem, enjoyment of school, academic outcomes) differed between the second-order factor and the composite score. Most importantly, in the second-order factor, some correlations were very high, implausible, or not computable, which was probably the result of the small variances of the second-order factor⁷. By contrast, the results of the composite score were more consistent throughout and largely similar across the different sets of the lower order self-concepts.

Discussion

The present research was aimed at comparing two competing theoretical representations of the Shavelson model (Shavelson et al., 1976): (a) a top-down approach in which global self-concept represents the cause of lower order self-concepts, implemented by a reflective model in terms of a traditional one-dimensional second-order factor model and (b) a bottom-up approach in which lower order self-concepts form a global self-concept, represented by a formative procedure in terms of a model-based latent composite score. Studies prior to this research investigated global self-concept almost exclusively from the perspective of reflective modeling approaches. Therefore, the present research contrasted the two theoretical ideas and included

⁷ In some of the analyses, the second-order factor model produced improper solutions or potentially questionable results (e.g., very low or very high standardized factor loadings of the second-order factor or nonpositive definite residual and latent variable covariance matrices; for an overview see Table A1, A2, A3). These results are not unreasonable by themselves, but they might rather be a symptom of the difficulties involved in the second-order factor model that resulted from the low or even negative correlations between the first-order factors.

three independent, large-scale studies (Study 1: $N = 8,063$; Study 2: $N = 3,081$; Study 3: $N = 2,106$) in order to empirically evaluate the respective methodological implementations.

Across the three studies (including varying sets of self-concepts and across two time points each), our results provided support for four major findings: First, the correlations between the lower order self-concepts were not consistently high. Particularly in conceptually distinct domains (e.g., math and verbal domains), the correlations were often low or sometimes even negative. Second, global (academic) self-concept as a composite score descriptively reproduced more interindividual differences. By contrast, in one case, the second-order factor resulted in a negative variance, and in another case, the second-order factor model did not even converge. Whenever academic self-concepts were included, the second-order factor explained less than 30% of the variance in the first-order factors on average. Third, the results on the stabilities as well as the results on the relations with external criteria indicated that the composite score typically revealed higher covariances than the second-order factor, whereas for the correlations, it was the opposite, due to the small variances in the second-order factors. Finally, some correlations in the second-order factor were not estimable, implausible, or surprisingly high (correlations of two academic self-concepts and self-esteem) or surprisingly low (e.g., correlations between two academic self-concepts and academic outcomes), whereas this was not the case for the composite score.

The present findings line up with previous studies, which showed that academic lower order self-concepts were barely or even negatively correlated, mirroring the effect described as the internal/external frame of reference effect (Marsh, 1986b; e.g., Marsh & Shavelson, 1985). These low and/or negative correlations contradicted the prerequisites for second-order factor models because second-order factors should be grounded on positive high intercorrelations between indicators (e.g., Bollen & Lennox, 1991). The small variances in the one-dimensional

second-order factors, which we found across all three studies, are likely the result of these low intercorrelations. Squeezing small correlations across lower order self-concepts into a common factor resulted in a variance-restricted second-order factor, which reproduced only small overall differences between individuals. Thus, such small-variance constructs are more narrow and provide less information about inter-individual differences, which can be reasonable when there is much construct-irrelevant variance in the indicators (here: first-order factors), but is problematic when the construct is supposed to cover a broad common range of the indicators. The low variances in the (one-dimensional) second-order factors fired back when we used the respective global (academic) self-concept for further analysis: The small variances dramatically influenced all standardized coefficients because of division by the variance, such as when looking at stabilities or correlations with external constructs. This could be problematic as it leads researchers to believe that there are high correlations when they are just artificially inflated. By contrast, the composite score did not depend on substantial intercorrelations between lower order self-concepts and was consequently better in depicting interindividual differences.

When reviewing the correlations with external criteria, we observed that the coefficients showed various incompatibilities with theoretical considerations. Theoretically, we would expect that global self-concept and global self-esteem would be more strongly correlated when considering a broader compared with a smaller spectrum of academic self-concepts. However, given the present findings in Studies 1 and 2, the correlations of the second-order factor with two different measures of self-esteem (Study 1: Rosenberg Self-Esteem Scale, Rosenberg, 1965; Study 2: Self-esteem scale from the children's quality of life scale [KINDL], Ravens-Sieberer et al., 2001) increased when fewer academic self-concepts were included. More specifically, when only math and German self-concept were included, the correlations between the second-order factor and self-esteem were surprisingly high ($r = .61$ to $.78$). This could indicate that students'

general feelings of worth are to a large extent determined by how they perceive their abilities in math and German, which is questionable given previous findings on the relation between academic self-concept and self-esteem over time (Marsh & O'Mara, 2008; Trautwein et al., 2006). Over and above the correlations that contradicted previous theoretical and empirical findings, some of the correlations in the (one-dimensional) second-order factor model were factually not computable or were implausible. More specifically, in Study 3, the negative variance of the second-order factor, which was an artificial result of the negative intercorrelations between lower order self-concepts, made further analysis impossible. In Study 1, two correlations exceeded a value of 1, which was another finding that fell outside the plausible range. Interestingly, these correlations appeared not only when the set of self-concepts were barely correlated but also when there were substantial correlations between the included self-concepts.

Overall, when modeling global (academic) self-concept by a composite score, we revealed a more consistent and theoretically plausible pattern of results. More specifically, the relations with external criteria remained largely similar when additional self-concepts were included, there were no implausible correlations, and the sizes and patterns of the correlations were more in line with theoretical considerations and previous empirical findings on the self-concepts' relations with self-esteem, enjoyment of school, and academic outcomes (Marsh & O'Neill, 1984; Marsh & Yeung, 1998). For example, in Studies 1 and 2, when only math and German self-concepts were included, the correlations with self-esteem were medium to high in size ($r = .37$ to $.47$).

A Latent Composite Score Approach: A New Perspective on and for the Shavelson Model?

Research on the structure of self-concept has a vivid history, beginning in a dustbowl and subsequently sparked by Shavelson's, Marsh's, and Brunner's theoretical and empirical specifications (e.g., Brunner et al., 2010; Marsh, 1990; Marsh & Shavelson, 1985; Shavelson et

al., 1976). These developments have answered multiple questions and have led to important gains in the understanding of self-concept. Transferring concepts applied to the hierarchical structure of cognitive abilities, previous research on the hierarchy of self-concept has embraced the framework of confirmatory factor analysis. This analytical approach follows a top-down logic by which higher order construct cause lower order constructs. At the same time, theoretical ideas also suggested a bottom-up process by which lower order self-concepts form higher order self-concepts. One reason why this theoretical idea has not garnered much empirical interest is that statistical procedures for modeling bottom-up ideas (i.e., formative approaches) have not been very sophisticated. A method that was recently developed—the model-based latent composite score (Rose et al., 2019)—was responsible for the present turnaround.

Overall, three insights from the analyses might favor the composite score model over the conventional (one-dimensional) second-order factor model: (a) The composite score seemed to be better in depicting interindividual differences in global (academic) self-concept, (b) the composite score yielded more consistent correlations, given varying sets of self-concepts, and (c) the composite score resulted in a more plausible pattern of correlations with respect to their size and theoretical reasonableness. By contrast, the one-dimensional second-order factor models resulted in low variances in global (academic) self-concept that boosted correlations to surprisingly high and sometimes clearly implausible and impermissibly high values.

Hence, according to the present research, a latent composite score modeling approach could provide a new perspective in research on the structure of self-concept (i.e., studying the multidimensionality and hierarchy; see also Arens et al., 2020) and also stimulate further developments. A latent composite score approach suggests that global (academic) self-concept is formed by lower order self-concepts in such a way that individuals integrate and aggregate their self-concepts in different areas of life, and this results in a global evaluation of the self. This

explicitly allows researchers to study the compensational processes of domain-specific self-concepts in a global evaluation. For example, a student may have a negative self-concept in biology but a fairly positive global academic self-concept because of his/her positive self-concepts in foreign languages and math. Such a perspective indeed goes back to the foundation of psychological research, in which James (1890/1963) stated that individuals' global self-evaluation represents a weighted average of their self-evaluations in different areas of life. Finally, if global (academic) self-concept follows a formative process of formation, this would have implications for how to foster it (e.g., through interventions). Rather than intervening on the global (academic) self-concept directly, one could opt to intervene on lower order self-concepts that are unfavorably developed. Simultaneously, it would be possible to comprehensively examine compensational processes, such as the side effects of interventions (see Gaspard et al., 2016). In sum, the latent composite score modeling approach offers new ways to study the development of self-concepts while incorporating the assumptions of the multidimensional, hierarchical Shavelson model with global self-concept at the apex of the hierarchy (Shavelson et al., 1976).

Whereas educational research based on the Shavelson model has largely moved toward a focus on the academic section of the hierarchy of self-concepts, this latent composite score approach allows for a unification of the range of self-concepts, including both academic and nonacademic self-concepts, as originally proposed by Shavelson et al. (1976). Thus, the approach opens up the possibility of additive and compensational mechanisms between different academic and nonacademic self-concepts in the formation of a global self-concept. At the same time, the latent composite score approach is in line with findings from the Marsh/Shavelson model and the internal/external frame of reference model (Marsh, 1986b, 1987, 1990; Marsh & Shavelson, 1985; Shavelson & Marsh, 1986) because the composite score approach does not call for

substantial correlations between lower order self-concepts, such as math and verbal self-concept. Furthermore, the latent composite score approach is theoretically in line with a central characteristic of the Nested Marsh/Shavelson model (Brunner et al., 2009; Brunner et al., 2010) in that it is capable of incorporating both global academic and domain-specific self-concepts. Hence, a composite score approach unifies previous assumptions on the structure of self-concept by reframing the Shavelson model as a formation process. The present research was aimed at providing a starting point for this perspective, which needs to be followed by a more granulated understanding of the processes involved. More specifically, a more in-depth—and possibly a qualitative—analysis of how individuals form their global evaluation of the self might provide important fundamental knowledge about the validity of such a model as well as the possible processes that are involved in the formation of global self-concept.

Beyond Self-Concept: Theoretical Assumptions and Statistical Models

Although our study focused on self-concept, we believe that our approach might be of more general interest in educational psychology. Generally speaking, theoretical considerations about the underlying processes of constructs and research questions need to be more strongly connected to the application of statistical models (Borsboom et al., 2003; Rhemtulla et al., 2015, 2019). Whenever one expects a formation process, the latent variable in reflective models may not be appropriate to represent the construct of interest. In addition, even if researchers theoretically assume reflective processes, empirical results (e.g., low intercorrelations among lower order constructs) can challenge these reflective ideas. A conservative consequence could be that researchers end up refraining from modeling a higher order factor, such as in previous research on self-concept (e.g., Marsh, 1990; Rentzsch et al., 2016). However, by contrast, the higher order factor might also be formed by the lower order factors instead of being the cause of the lower order factors. Thus, a different modeling approach would be needed.

In educational psychology, reflective modeling approaches are the default procedure for modeling relations between higher and lower order constructs. In other fields of research, however, formative approaches for multidimensional hierarchical constructs are well established, for example, in management constructs such as strategy or job satisfaction (Law et al., 1998; Podsakoff et al., 2004). Formative approaches for multidimensional constructs might also be embraced more intensively by future psychological research. This needs to start by giving deeper consideration to the ontology of multidimensional constructs. In addition, when there are low correlations between lower order dimensions, this strongly suggests formative considerations. In this regard, even the facade of the psychological pioneer research field in confirmatory factor analysis, the field of intellectual abilities, recently began to crumble with regard to their long-standing tradition of using reflective higher order models (Conway & Kovacs, 2015; Eid et al., 2017). Very recently, considerations of formative constructs have also been stressed in the field of domain knowledge (Stadler et al., 2021). In addition, a recent paper in developmental psychology demonstrated that the alternative measurement of executive functioning (confirmatory factor analysis vs. composite score) led to different results when it came to relations with academic achievement (Camerota et al., 2020). In educational psychology, the relevance of formative approaches might be particularly important, given the wide range of multidimensional, hierarchical constructs in this field. On the one hand, this could apply to global constructs that arise from perceptions across different school subjects, which also face dimensional comparison processes, such as interest, effort, or students' perceptions of teaching quality (e.g., Arens & Möller, 2016; Jaekel et al., 2020). On the other hand, more globally speaking, this could apply to global constructs that are not unidimensional due to the specificity of their components such as task values (Gaspard et al., 2015; Gaspard et al., 2017), or, in line with research on job satisfaction, this could apply to students' school satisfaction.

Limitations and Future Directions

We analyzed the consequences of top-down and bottom-up representations of the Shavelson model in a comprehensive research framework using multiple studies, multiple sets of self-concepts, and two time points each. This research was aimed at providing a new perspective for rethinking global self-concept. However, there are some limitations that need to be taken into account.

First, it is important to consider the selection of self-concepts. In line with the Shavelson model, we covered both academic and nonacademic self-concepts. However, the self-concept domains we used varied across the three studies in the present research. This variation in turn led to different meanings of the global factors in the three studies. Moreover, the self-concept domains used in this research were by no means exhaustive. Shavelson and colleagues already emphasized that their illustration of the structure of self-concept is just one possible representation of the universe of self-concepts (Shavelson et al., 1976). In contrast to reflective models, which would assume that indicators are exchangeable because they are caused by one common factor, the selection of indicators is decisive in a formative modeling procedure (Bollen & Lennox, 1991). Here, the selection of self-concepts fully constitutes the global factor (i.e., [academic] global self-concept), and therefore, the composite score needs to be interpreted in the wake of its constitutional elements (i.e., the measured self-concept domains). For example, when only academic self-concepts are included, the composite score reflects global academic self-concept, whereas when only nonacademic self-concepts are included, the composite score represents global nonacademic self-concept. Moreover, when it comes to the selection of different self-concepts (when applying the LCS model), three intertwined steps must be considered. First, the global construct of interest needs to be set (i.e., global self-concept, global academic self-concept, or even a more specific “global” self-concept, such as the global sport

self-concept) and should depict a precisely defined construct. Second, the target population (e.g., age, social backgrounds) as well as varying contexts (e.g., school or work) must be considered. Finally, after setting the global target construct and defining the target population, the relevant areas or domains must be derived from the definition of the construct while considering the environmental factors of the target population (e.g., during the secondary school years, global academic self-concept is [predominantly] constituted through the self-concepts from the specific school subjects). In the present study, the results of the relations between the composite score and external criteria differed in particular with regard to the inclusion of nonacademic self-concepts. For example, global self-esteem seemed to be most strongly related to a global self-concept whenever we included nonacademic self-concepts, which is in line with previous findings (e.g., Donnellan et al., 2007; Harter, 2003). At the same time, the correlations were largely similar across different sets of academic self-concepts. However, future research using different sets of self-concepts needs to test the robustness of this pattern of results. In addition, we focused our research on the relations between several domain-specific self-concepts and global (academic) self-concept, whereas we did not address self-concept measures on a more granulated subdomain or behavioral level (for this approach, see Arens & Jansen, 2016; Lau et al., 1999; Schroeders & Jansen, 2020; Seeshing Yeung et al., 2000). Yet, combining these different hierarchical levels can be a promising focus in future research in order to gain a more comprehensive picture of bottom-up and/or top-down processes at more granulated levels of the self-concept hierarchy.

Second, because this was the first application of the model-based latent composite score, we gave all self-concepts equal weights. Although this is probably not an applicable assumption from a theoretical perspective, results from other research domains (e.g., life satisfaction; see Rohrer & Schmukle, 2018 or human vs. statistical predictions; see Wainer, 1976) have shown that unit-weights are relatively robust and might be a justifiable procedure. By contrast, in the

second-order factor model, weights (i.e., the factor loadings of the second-order factor) were estimated, and hence, they differed across the lower order self-concepts. In the composite score model, these weights needed to be assigned in advance, and therefore, they needed to be a result of a priori considerations. For example, if, in future research, we aimed to construct the indicator of global self-concept that is the most similar to measures of global self-esteem, the present results suggest that nonacademic self-concepts need to be given more weight than academic self-concepts. Another stream of research proposed to extend the Shavelson model by considering the individual importance of the lower order self-concepts (James, 1890/1963). Despite the fact that empirical studies have failed to find support for this model using second-order factor models (Marsh, 1986a; Marsh & Scalas, 2018; Scalas et al., 2013), this could be a direction for future research using a latent composite score approach.

Third, previous research has argued that top-down models should be tested against bottom-up models by using multiwave-multivariable structural equation modeling, such as cross-lagged panel models (Harris et al., 2018; Marsh & O'Mara, 2008; Marsh & Yeung, 1998; Rentzsch & Schröder-Abé, 2018; Trautwein et al., 2006). This field of research has tested ideas that are conceptually similar to those from the present study with temporal predictions across yearly waves of assessment. In contrast to the present study, these studies (a) focused on processes over time rather than the directional link *within* the hierarchy of self-concept and (b) used unidimensional global self-esteem as an indicator of global self-concept. However, it is unclear whether this unidimensional measure of global self-esteem provides the optimal operationalization of the apex of the Shavelson hierarchy. Future research could merge our approach with longitudinal predictions in order to explain how lower order self-concepts and global self-concept, modeled as a composite score, as well as unidimensional global self-esteem are related over time. This could enrich our understanding about not only the prospective

relations between lower and higher order self-concepts but also the similarities and differences between global self-concept and global self-esteem.

Finally, in the present manuscript, we compared two different methodological implementations (the traditional one-dimensional second-order factor model and the latent composite score model) of the hierarchy of self-concept in which we explicitly modeled global (academic) self-concept. However, there have been other fruitful modeling procedures that have been applied to the structure of self-concept (for an overview, see Arens et al., 2020). As described in the theoretical background section, one of these modeling procedures is the Nested Marsh/Shavelson model (Brunner et al., 2010). In order to be fully transparent and to provide an overall picture of our analyses, the results from the Nested Marsh/Shavelson model are included in Appendix B. However, the Nested Marsh/Shavelson model requires an additional direct measure (i.e., multiple items) of the global construct, which was not the core idea of the present manuscript. Yet, overall, rather than narrowing this research field to one specific model, we believe that a broadening of the perspective to include different modeling procedures will be inevitable given that each of these models has theoretical and methodological advantages as well as restrictions.⁸

Conclusion

The present research was aimed at integrating theoretical considerations and statistical modeling approaches in the implementation of global (academic) self-concept. We proposed that the previous focus on conventional reflective modeling procedures (e.g., one-dimensional second-order factor models) be opened up to new perspectives, such as those involving model-

⁸ The different modeling procedures on the nature of global self-concept (e.g., the one-dimensional second-order factor model, the latent composite score model, and the Nested Marsh/Shavelson model) are all largely in line with the characteristics of self-concept proposed by the Shavelson et al (1976). Yet, the different models target different formation procedures of global self-concept, which can have diverging implications for the predictions made by these models.

based latent composite scores. Over and above research on self-concept, the present findings should pave the way for turnarounds in the analyses of multidimensional, hierarchical constructs: Theoretical considerations of bottom-up processes combined with their empirical foundations (e.g., low correlations between the lower order dimensions) should lead researchers to consider implementations that use formative modeling approaches (e.g., the model-based latent composite score). According to our research, for students such as Jasmin and Rafael, instead of their domain-specific self-concepts being determined by their global self-concept, these students rather aggregate their self-concepts in different areas of their lives in order to generate a global self-concept. A more granulated understanding of Jasmin's and Rafael's self-concept formation processes needs to build the foundation of future self-concept research.

References

Arens, A. K., & Jansen, M. (2016). Self-concepts in reading, writing, listening, and speaking: A multidimensional and hierarchical structure and its generalizability across native and foreign languages. *Journal of Educational Psychology*, 108(5), 646–664.

<https://doi.org/10.1037/edu0000081>

Arens, A. K., Jansen, M., Preckel, F., Schmidt, I., & Brunner, M. (2020). The structure of academic self-concept: A methodological review and empirical illustration of central models. *Review of Educational Research*. Advance online publication.

<https://doi.org/10.3102/0034654320972186>

Arens, A. K., & Möller, J. (2016). Dimensional comparisons in students' perceptions of the learning environment. Advance online publication.

<https://doi.org/10.1016/J.LEARNINSTRUC.2015.11.001> (Learning and Instruction, 42, 22-30).

Baumert, J., Roeder, P. M., Gruehn S., Heyn S., Köller, O., Rimmel, R., Schnabel, K. U., & Seipp, B. (1996). Bildungsverläufe und psychosoziale Entwicklung im Jugendalter (BIJU) [Learning processes, educational careers, and psychosocial development in adolescence]. In K. P. Treumann, G. Neubauer, R. Möller, & J. Abel (Eds.), *Methoden und Anwendungen empirischer pädagogischer Forschung* (pp. 170–180). Waxmann.

Blalock, H. M. (1964). *Causal inferences in nonexperimental research*. University of North Carolina Press.

- Bollen, K., & Lennox, R. (1991). Conventional wisdom on measurement: A structural equation perspective. *Psychological Bulletin*, 110(2), 305–314. <https://doi.org/10.1037/0033-2909.110.2.305>
- Bollen, K. A., & Bauldry, S. (2011). Three cs in measurement models: Causal indicators, composite indicators, and covariates. *Psychological Methods*, 16(3), 265–284. <https://doi.org/10.1037/a0024448>
- Bollen, K. A., & Diamantopoulos, A. (2017). In defense of causal-formative indicators: A minority report. *Psychological Methods*, 22(3), 581–596. <https://doi.org/10.1037/met0000056>
- Borsboom, D. (2008). Latent variable theory. *Measurement: Interdisciplinary Research and Perspectives*, 6(1-2), 25–53. <https://doi.org/10.1080/15366360802035497>
- Borsboom, D., Mellenbergh, G. J., & van Heerden, J. (2003). The theoretical status of latent variables. *Psychological Review*, 110(2), 203–219. <https://doi.org/10.1037/0033-295X.110.2.203>
- Borsboom, D., Mellenbergh, G. J., & van Heerden, J. (2004). The concept of validity. *Psychological Review*, 111(4), 1061–1071. <https://doi.org/10.1037/0033-295X.111.4.1061>
- Brosseau-Liard, P. E., & Savalei, V. (2014). Adjusting incremental fit indices for nonnormality. *Multivariate Behavioral Research*, 49(5), 460–470. <https://doi.org/10.1080/00273171.2014.933697>
- Brosseau-Liard, P. E., Savalei, V., & Li, L. (2012). An investigation of the sample performance of two nonnormality corrections for rmsea. *Multivariate Behavioral Research*, 47(6), 904–930. <https://doi.org/10.1080/00273171.2012.715252>

- Brown, J. D. (1993). Self-esteem and self-evaluations: Feeling is believing. In J. Suls (Ed.), *Psychological perspectives on the self* (Vol. 4, pp. 27–58). Erlbaum Press.
- Brunner, M., Keller, U., Dierendonck, C., Reichert, M., Ugen, S., Fischbach, A., & Martin, R. (2010). The structure of academic self-concepts revisited: The nested marsh/shavelson model. *Journal of Educational Psychology, 102*(4), 964–981. <https://doi.org/10.1037/a0019644>
- Brunner, M., Keller, U., Hornung, C., Reichert, M., & Martin, R. (2009). The cross-cultural generalizability of a new structural model of academic self-concepts. *Learning and Individual Differences, 19*(4), 387–403. <https://doi.org/10.1016/j.lindif.2008.11.008>
- Brunner, M., Lüdtke, O., & Trautwein, U. (2008). The internal/external frame of reference model revisited: Incorporating general cognitive ability and general academic self-concept. *Multivariate Behavioral Research, 43*(1), 137–172. <https://doi.org/10.1080/00273170701836737>
- Camerota, M., Willoughby, M. T., & Blair, C. B. (2020). Measurement models for studying child executive functioning: Questioning the status quo. *Developmental Psychology*. Advance online publication. <https://doi.org/10.1037/dev0001127>
- Campbell, D. T., & Fiske, D. W. (1959). Convergent and discriminant validation by the multitrait-multimethod matrix. *Psychological Bulletin, 56*(2), 81–105. <https://doi.org/10.1037/h0046016>
- Cole, D. A., Ciesla, J. A., & Steiger, J. H. (2007). The insidious effects of failing to include design-driven correlated residuals in latent-variable covariance structure analysis. *Psychological Methods, 12*(4), 381–398. <https://doi.org/10.1037/1082-989X.12.4.381>

- Cole, D. A., & Preacher, K. J. (2014). Manifest variable path analysis: Potentially serious and misleading consequences due to uncorrected measurement error. *Psychological Methods*, 19(2), 300–315. <https://doi.org/10.1037/a0033805>
- Conway, A. R. A., & Kovacs, K. (2015). New and emerging models of human intelligence. *Wiley Interdisciplinary Reviews: Cognitive Science*, 6(5), 419–426. <https://doi.org/10.1002/wcs.1356>
- Coopersmith, S. (1967). *The antecedents of self-esteem*. W. H. Freeman.
- Diamantopoulos, A., Riefler, P., & Roth, K. P. (2008). Advancing formative measurement models. *Journal of Business Research*, 61(12), 1203–1218. <https://doi.org/10.1016/j.jbusres.2008.01.009>
- Donnellan, M. B., Trzesniewski, K. H., Conger, K. J., & Conger, R. D. (2007). A three-wave longitudinal study of self-evaluations during young adulthood. *Journal of Research in Personality*, 41(2), 453–472. <https://doi.org/10.1016/j.jrp.2006.06.004>
- Donnellan, M. B., Trzesniewski, K. H., & Robins, R. W. (2011). Self-esteem: Enduring issues and controversies. In T. Chamorro-Premuzic (Ed.), *The wiley-blackwell handbook of individual differences* (pp. 718–746). Wiley-Blackwell.
- Edwards, J. R., & Bagozzi, R. P. (2000). On the nature and direction of relationships between constructs and measures. *Psychological Methods*, 5(2), 155–174. <https://doi.org/10.1037/1082-989X.5.2.155>
- Eid, M., Geiser, C., Koch, T., & Heene, M. (2017). Anomalous results in g-factor models: Explanations and alternatives. *Psychological Methods*, 22(3), 541–562. <https://doi.org/10.1037/met0000083>

- Eid, M., Lischetzke, T., Nussbeck, F. W., & Trierweiler, L. I. (2003). Separating trait effects from trait-specific method effects in multitrait-multimethod models: A multiple-indicator c(t-1) model. *Psychological Methods*, 8(1), 38–60. <https://doi.org/10.1037/1082-989X.8.1.38>
- Fend, H., & Prieser, H.-G. (Eds.). (1986). *Dokumentation der Skalen des Projekts "Entwicklung im Jugendalter" [Documentation of the instruments of the project "Development in adolescence"]*. Sozialwissenschaftliche Fakultät der Universität Konstanz.
- Fitts, W. H. (1965). *A manual for the Tennessee Self-Concept Scale*. Counselor Recordings and Tests.
- Gaspard, H., Dicke, A.-L., Flunger, B., Häfner, I., Brisson, B. M., Trautwein, U., & Nagengast, B. (2016). Side effects of motivational interventions? Effects of an intervention in math classrooms on motivation in verbal domains. *AERA Open*, 2(2), 233285841664916. <https://doi.org/10.1177/2332858416649168>
- Gaspard, H., Dicke, A.-L., Flunger, B., Schreier, B., Häfner, I., Trautwein, U., & Nagengast, B. (2015). More value through greater differentiation: Gender differences in value beliefs about math. *Journal of Educational Psychology*, 107(3), 663–677. <https://doi.org/10.1037/edu0000003>
- Gaspard, H., Häfner, I., Parrisius, C., Trautwein, U., & Nagengast, B. (2017). Assessing task values in five subjects during secondary school: Measurement structure and mean level differences across grade level, gender, and academic subject. *Contemporary Educational Psychology*, 48, 67–84. <https://doi.org/10.1016/j.cedpsych.2016.09.003>

- Gignac, G. E., & Szodorai, E. T. (2016). Effect size guidelines for individual differences researchers. *Personality and Individual Differences*, 102(7), 74–78.
<https://doi.org/10.1016/j.paid.2016.06.069>
- Greenwald, A. G. (2012). There is nothing so theoretical as a good method. *Perspectives on Psychological Science*, 7(2), 99–108. <https://doi.org/10.1177/1745691611434210>
- Harris, M. A., Wetzel, E., Robins, R. W., Donnellan, M. B., & Trzesniewski, K. H. (2018). The development of global and domain self-esteem from ages 10 to 16 for mexican-origin youth. *International Journal of Behavioral Development*, 42(1), 4–16.
<https://doi.org/10.1177/0165025416679744>
- Harter, S. (2003). The development of self-representations during childhood and adolescence. In M. R. Leary & J. P. Tangney (Eds.), *Handbook of self and identity* (pp. 610–642). Wiley.
- Hishiki, P. C. (1969). Self-concepts of 6th-grade girls of mexican-American descent. *California Journal of Educational Research*(20), 56–62.
- Jackel, A., Göllner, R., & Trautwein, U. (2020). How students' perceptions of teaching quality in one subject are impacted by the grades they receive in another subject: Dimensional comparisons in student evaluations of teaching quality. *Journal of Educational Psychology*. Advance online publication. <https://doi.org/10.1037/EDU0000488>
- James, W. (1890/1963). *The principles of psychology*. Holt, Rinehart & Winston.
- Jerusalem, M. (1984). *Selbstbezogene Kognitionen in schulischen Bezugsgruppen: Eine Längsschnittstudie [Self-related cognitions in school contexts]*. Freie Universität Berlin, Institut für Psychologie.

- Jonkmann, K., Rose, N., & Trautwein, U. (Eds.). (2013). *Tradition und Innovation: Entwicklungsverläufe an Haupt- und Realschulen in Baden-Württemberg und Mittelschulen in Sachsen - Abschlussbericht für die Länder Baden-Württemberg und Sachsen [Tradition and innovation: Academic and psychosocial development in vocational track schools in the states of Baden-Württemberg and Sachsen]*. Unpublished project report, University of Tübingen.
- Jopt, U.-J. (1978). *Selbstkonzept und Ursachenerklärung in der Schule: Zur Attribuierung von Schulleistungen [Self-concept and explanation of causes in school: On the attribution of school performance]*. Kamp.
- Lau, I. C.-y., Yeung, A. S., Jin, P., & Low, R. (1999). Toward a hierarchical, multidimensional english self-concept. *Journal of Educational Psychology*, 91(4), 747–755.
<https://doi.org/10.1037/0022-0663.91.4.747>
- Law, K. S., Wong, C.-S., & Mobley, W. M. (1998). Toward a taxonomy of multidimensional constructs. *Academy of Management Review*, 23(4), 741–755.
<https://doi.org/10.5465/amr.1998.1255636>
- Little, T. D., Slegers, D. W., & Card, N. A. (2006). A non-arbitrary method of identifying and scaling latent variables in sem and macs models. *Structural Equation Modeling: A Multidisciplinary Journal*, 13(1), 59–72. https://doi.org/10.1207/s15328007sem1301_3
- Ludwig, D. J., & Maehr, M. L. (1967). Changes in self concept and stated behavioral preferences. *Child Development*, 38(2), 453. <https://doi.org/10.2307/1127302>
- Marsh, H. W. (1986a). Global self-esteem: Its relation to specific facets of self-concept and their importance. *Journal of Personality and Social Psychology*, 51(6), 1224–1236.
<https://doi.org/10.1037/0022-3514.51.6.1224>

Marsh, H. W. (1986b). Verbal and math self-concepts: An internal/external frame of reference model. *American Educational Research Journal*, 23(1), 129–149.

<https://doi.org/10.3102/00028312023001129>

Marsh, H. W. (1987). The hierarchical structure of self-concept and the application of hierarchical confirmatory factor analysis. *Journal of Educational Measurement*, 24(1), 17–39.

<https://doi.org/10.1111/j.1745-3984.1987.tb00259.x>

Marsh, H. W. (1989). Age and sex effects in multiple dimensions of self-concept: Preadolescence to early adulthood. *Journal of Educational Psychology*, 81(3), 417–430.

<https://doi.org/10.1037/0022-0663.81.3.417>

Marsh, H. W. (1990). The structure of academic self-concept: The marsh/shavelson model.

Journal of Educational Psychology, 82(4), 623–636. <https://doi.org/10.1037/0022-0663.82.4.623>

Marsh, H. W., & Ayotte, V. (2003). Do multiple dimensions of self-concept become more differentiated with age? The differential distinctiveness hypothesis. *Journal of Educational Psychology*, 95(4), 687–706. <https://doi.org/10.1037/0022-0663.95.4.687>

Marsh, H. W., & Craven, R. (1997). Academic self-concept. In G. D. Phye (Ed.), *Handbook of classroom assessment: learning, achievement, and adjustment* (pp. 131–198). Academic Press.

<https://doi.org/10.1016/B978-012554155-8/50008-9>

Marsh, H. W., Craven, R. G., & Debus, R. (1991). Self-concepts of young children 5 to 8 years of age: Measurement and multidimensional structure. *Journal of Educational Psychology*, 83(3),

377–392. <https://doi.org/10.1037/0022-0663.83.3.377>

- Marsh, H. W., & Hattie, J. A. (1996). Theoretical models in self-concept. In B. Bracken (Ed.), *Handbook of self-concept* (pp. 38–90). Erlbaum.
- Marsh, H. W., & Hau, K.-T. (1996). Assessing goodness of fit. *The Journal of Experimental Education*, 64(4), 364–390. <https://doi.org/10.1080/00220973.1996.10806604>
- Marsh, H. W., & Hau, K.-T. (2004). Explaining paradoxical relations between academic self-concepts and achievements: Cross-cultural generalizability of the internal/external frame of reference predictions across 26 countries. *Journal of Educational Psychology*, 96(1), 56–67. <https://doi.org/10.1037/0022-0663.96.1.56>
- Marsh, H. W., & Hau, K.-T. (2007). Applications of latent-variable models in educational psychology: The need for methodological-substantive synergies. *Contemporary Educational Psychology*, 32(1), 151–170. <https://doi.org/10.1016/j.cedpsych.2006.10.008>
- Marsh, H. W., & Hocevar, D. (1985). Application of confirmatory factor analysis to the study of self-concept: First- and higher order factor models and their invariance across groups. *Psychological Bulletin*, 97(3), 562–582. <https://doi.org/10.1037/0033-2909.97.3.562>
- Marsh, H. W., & O'Mara, A. (2008). Reciprocal effects between academic self-concept, self-esteem, achievement, and attainment over seven adolescent years: Unidimensional and multidimensional perspectives of self-concept. *Personality and Social Psychology Bulletin*, 34(4), 542–552. <https://doi.org/10.1177/0146167207312313>
- Marsh, H. W., & O'Neill, R. (1984). Self description questionnaire iii: The construct validity of multidimensional self-concept ratings by late adolescents. *Journal of Educational Measurement*, 21(2), 153–174. <https://doi.org/10.1111/j.1745-3984.1984.tb00227.x>

- Marsh, H. W., & Scalas, L. F. (2018). Individually weighted-average models: Testing a taxonomic sem approach across different multidimensional/global constructs because the weights “don’t make no nevermind”. *Structural Equation Modeling: A Multidisciplinary Journal*, 25(1), 137–159. <https://doi.org/10.1080/10705511.2017.1370377>
- Marsh, H. W., & Shavelson, R. (1985). Self-concept: Its multifaceted, hierarchical structure. *Educational Psychologist*, 20(3), 107–123. https://doi.org/10.1207/s15326985ep2003_1
- Marsh, H. W., & Yeung, A. S. (1998). Longitudinal structural equation models of academic self-concept and achievement: Gender differences in the development of math and english constructs. *American Educational Research Journal*, 35(4), 705–738. <https://doi.org/10.3102/00028312035004705>
- McNeish, D., Stapleton, L. M., & Silverman, R. D. (2017). On the unnecessary ubiquity of hierarchical linear modeling. *Psychological Methods*, 22(1), 114–140. <https://doi.org/10.1037/met0000078>
- Meredith, W. (1993). Measurement invariance, factor analysis and factorial invariance. *Psychometrika*, 58(4), 525–543. <https://doi.org/10.1007/BF02294825>
- Morin, A. J. S., Arens, A. K., & Marsh, H. W. (2016). A bifactor exploratory structural equation modeling framework for the identification of distinct sources of construct-relevant psychometric multidimensionality. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(1), 116–139. <https://doi.org/10.1080/10705511.2014.961800>
- Muthén, B. O., & Satorra, A. (1995). Complex sample data in structural equation modeling. *Sociological Methodology*, 25, 267. <https://doi.org/10.2307/271070>
- Muthén, L. K., & Muthén, B. O. (1998-2017). *Mplus user’s guide (8th ed.)*. Muthén & Muthén.

- Nagengast, B., Trautwein, U., Kelava, A., & Lüdtke, O. (2013). Synergistic effects of expectancy and value on homework engagement: The case for a within-person perspective. *Multivariate Behavioral Research*, 48(3), 428–460. <https://doi.org/10.1080/00273171.2013.775060>
- Podsakoff, N. P., Shen, W., & Podsakoff, P. M. (2004). The role of formative measurement models in strategic management research: Review, critique, and implications for future research. In D. J. Ketchen & D. D. Bergh (Eds.), *Research methodology in strategy and management* (Vol. 3, pp. 197–252). Elsevier. [https://doi.org/10.1016/S1479-8387\(06\)03008-6](https://doi.org/10.1016/S1479-8387(06)03008-6)
- Ravens-Sieberer, U., Gosch, A., Abel, T., Auquier, P., Bellach, B.-M., Bruil, J., Dr, W., Power, M., & Rajmil, L. (2001). Quality of life in children and adolescents: a European public health perspective. *Sozial- Und Präventivmedizin SPM*, 46(5), 294–302. <https://doi.org/10.1007/BF01321080>
- Rentsch, K., & Schröder-Abé, M. (2018). Stability and change in domain-specific self-esteem and global self-esteem. *European Journal of Personality*, 32(4), 353–370. <https://doi.org/10.1002/per.2167>
- Rentsch, K., Wenzler, M. P., & Schütz, A. (2016). The structure of multidimensional self-esteem across age and gender. *Personality and Individual Differences*, 88, 139–147. <https://doi.org/10.1016/j.paid.2015.09.012>
- Rhemtulla, M., van Bork, R., & Borsboom, D. (2015). Calling models with causal indicators “measurement models” implies more than they can deliver. *Measurement: Interdisciplinary Research and Perspectives*, 13(1), 59–62. <https://doi.org/10.1080/15366367.2015.1016343>

- Rhemtulla, M., van Bork, R., & Borsboom, D. (2019). Worse than measurement error: Consequences of inappropriate latent variable measurement models. *Psychological Methods*. Advance online publication. <https://doi.org/10.1037/met0000220>
- Rohrer, J. M., & Schmukle, S. C. (2018). Individual importance weighting of domain satisfaction ratings does not increase validity. *Collabra. Psychology*, 4(1). <https://doi.org/10.1525/collabra.116>
- Rose, N., Wagner, W., Mayer, A., & Nagengast, B. (2019). Model-based manifest and latent composite scores in structural equation models. *Collabra: Psychology*, 5(1), 9. <https://doi.org/10.1525/collabra.143>
- Rosenberg, M. (1965). *Society and the adolescent self-image*. Princeton University Press.
- Scalas, L. F., Marsh, H. W., Nagengast, B., & Morin, A. J. S. (2013). Latent-variable approaches to the jamesian model of importance-weighted averages. *Personality and Social Psychology Bulletin*, 39(1), 100–114. <https://doi.org/10.1177/0146167212465321>
- Schroeders, U., & Jansen, M. (2020). Science self-concept – more than the sum of its parts? *The Journal of Experimental Education*, 1–17. <https://doi.org/10.1080/00220973.2020.1740967>
- Sears, P. S., Adenubi, M., Block, M., Crist, J., Gamble, J., & Hubner, J. J. (1972). *Effective reinforcement for achievement behaviors in disadvantaged children: The first year. Technical Report No. 30*. Stanford Center for Research and Development in Teaching, 1972. (ERIC Document Reproduction Service No. ED 067 442).
- Seeshing Yeung, A., Chui, H.-S., Lau, I. C.-y., McInerney, D. M., Russell-Bowie, D., & Suliman, R. (2000). Where is the hierarchy of academic self-concept? *Journal of Educational Psychology*, 92(3), 556–567. <https://doi.org/10.1037/0022-0663.92.3.556>

Shavelson, R. J., Hubner, J. J., & Stanton, G. C. (1976). Self-concept: Validation of construct interpretations. *Review of Educational Research*, 46(3), 407–441.

<https://doi.org/10.3102/00346543046003407>

Shavelson, R. J., & Marsh, H. W. (1986). On the structure of self-concept. In R. Schwarzer (Ed.), *Anxiety and cognition* (pp. 305–330). Lawrence Erlbaum Associates, Inc.

Soares, A. T., & Soares, L. M. (1969). Self-perceptions of culturally disadvantaged children. *American Educational Research Journal*, 6(1), 31–45.

<https://doi.org/10.3102/00028312006001031>

Soares, L. M., & Soares, A. T. (1977). The self-concept: Mini, maxi, multi ? *Paper Presented at the Annual Meeting of the American Educational Research Association, New York.*

Stadler, M., Sailer, M., & Fischer, F. (2021). Knowledge as a formative construct: A good alpha is not always better. *New Ideas in Psychology*, 60, 100832.

<https://doi.org/10.1016/j.newideapsych.2020.100832>

Swann, W. B., Chang-Schneider, C., & Larsen McClarty, K. (2007). Do people's self-views matter? Self-concept and self-esteem in everyday life. *American Psychologist*, 62(2), 84–94.

<https://doi.org/10.1037/0003-066X.62.2.84>

Trautwein, U. (2003). *Schule und Selbstwert [Schools and self-esteem]*. Waxmann.

Trautwein, U., Lüdtke, O., Köller, O., & Baumert, J. (2006). Self-esteem, academic self-concept, and achievement: How the learning environment moderates the dynamics of self-concept.

Journal of Personality and Social Psychology, 90(2), 334–349. <https://doi.org/10.1037/0022-3514.90.2.334>

- Trautwein, U., Nagy, G., & Maaz, K. (2011). Soziale disparitäten und die öffnung des sekundarschulsystems [social disparities and the opening of the secondary school system in Germany - a study of the transition from lower to upper secondary education]. *Zeitschrift Für Erziehungswissenschaft*, 14(3), 445–463. <https://doi.org/10.1007/s11618-011-0220-5>
- Vernon, P. E. (1950). *The structure of human abilities*. Wiley.
- Wainer, H. (1976). Estimating coefficients in linear models: It don't make no nevermind. *Psychological Bulletin*, 83(2), 213–217. <https://doi.org/10.1037/0033-2909.83.2.213>
- Zirkel, P. A. (1971). Self-concept and the “disadvantage” of ethnic group membership and mixture. *Review of Educational Research*, 41(3), 211–225. <https://doi.org/10.3102/00346543041003211>

Table 1
Overview of the Self-Concept Measures in the Three Studies

Self-concept	Study 1: BIJU				Study 2: TRAIN				Study 3: TOSCA-10			
	Num. of Items	α (T1, T2)	Range of λ_s^a	Example	Num. of Items	α (T1, T2)	Range of λ_s^a	Example	Num. of Items	α (T1, T2)	Range of λ_s^a	Example
Academic												
Math	4	.85, .90	.64, .86		4	.78, .86	.62, .82	“I am good at mathematics /German /English.”	4	.89, .91	.72, .94	“I am good at mathematics.”
German/Verbal	4	.77, .87	.51, .83	“I don’t like mathematics/ German/English/ Biology/Physics very much.”	4	.64, .66	.28, .82		4	.76, .80	.53, .79	“I can express myself verbally well.”
English	4	.83, .88	.58, .84		4	.68, .84	.51, .84		4	.92, .92	.76, .93	“I am good at English.”
Biology	4	.87, .88	.64, .86									
Physics	4	.89, .89	.69, .86									
Economic									4	.84, .89	.65, .89	“I understand economic affairs well.”
Technical									8	.94, .93	.72, .88	“I find it easy to solve technical problems.”
Nonacademic												
Social	4	.69, .69	.19, .80	“I am quite respected among my classmates.”	4	.70, .83	.37, .86	“I am quite respected among my classmates.”				
Appearance	4	.47, .39	.09, .74	“I am quite satisfied with my physical development”								
Assertiveness	3	.57, .62	.46, .70	“I don't think I can assert myself as well as other people.”	3	.66, .76	.54, .81	“I don't think I can assert myself as well as other people.”				

Note. ^a λ_s = standardized factor loadings (extracted from correlated first-order factors models).

Table 2

Latent Intercorrelations of the First-Order Self-Concepts in the BIJU Study

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Math T1	-														
2. German T1	.21	-													
3. English T1	.16	.24	-												
4. Biology T1	.15	.31	.17	-											
5. Physics T1	.41	.22	.18	.45	-										
6. Social T1	.16	.25	.27	.20	.13	-									
7. Appearance T1	.29	.19	.24	.21	.32	.67	-								
8. Assertiveness T1	.20	.23	.22	.18	.21	.63	.55	-							
9. Math T2	.51	.13	.12	.14	.32	.13	.25	.16	-						
10. German T2	.09	.49	.15	.24	.17	.20	.14	.15	.23	-					
11. English T2	.14	.22	.58	.14	.18	.21	.19	.11	.17	.28	-				
12. Biology T2	.17	.17	.11	.39	.25	.14	.15	.09	.27	.29	.15	-			
13. Physics T2	.31	.12	.14	.19	.44	.10	.24	.14	.40	.21	.20	.41	-		
14. Social T2	.08	.13	.16	.12	.06	.53	.30	.31	.19	.23	.22	.21	.15	-	
15. Appearance T2	.19	.12	.18	.10	.21	.38	.59	.30	.28	.18	.25	.20	.28	.73	-
16. Assertiveness T2	.14	.15	.14	.12	.14	.43	.31	.52	.24	.23	.22	.24	.22	.77	.72

Note. $N = 8,063$.

Table 3

Latent Intercorrelations of the First-Order Self-Concepts in the TRAIN Study

	1	2	3	4	5	6	7	8	9
1. Math T1	-								
2. German T1	.29	-							
3. English T1	.18	.45	-						
4. Social T1	.27	.31	.33	-					
5. Assertiveness T1	.34	.39	.32	.65	-				
6. Math T2	.42	-.00	.01	-.01	.05	-			
7. German T2	.18	.50	.29	.15	.14	.22	-		
8. English T2	.08	.27	.36	.10	.06	-.01	.42	-	
9. Social T2	.18	.20	.17	.36	.29	.10	.26	.21	-
10. Assertiveness T2	.27	.19	.15	.26	.34	.17	.23	.21	.53

Note. $N = 3,033$.

Table 4

Latent Intercorrelations of the First-Order Self-Concepts in the TOSCA-10 Study

	1	2	3	4	5	6	7	8	9
1. Math T1	-								
2. Verbal T1	-.31	-							
3. English T1	-.27	.62	-						
4. Economic T1	.14	.19	.07	-					
5. Technical T1	.28	-.25	-.23	.14	-				
6. Math T2	.79	-.26	-.22	.13	.30	-			
7. Verbal T2	-.31	.71	.56	.23	-.21	-.25	-		
8. English T2	-.21	.51	.67	.09	-.15	-.17	.64	-	
9. Economic T2	.16	.13	.12	.47	.00	.31	.29	.19	-
10. Technical T2	.27	-.20	-.19	.08	.78	.33	-.14	-.12	-.01

Note. $N = 2,098$.

Table 5

Means and (Explained Proportions of) Variances of the Second-Order Factor and the Composite Score

Set of self-concepts	Global (academic) self-concept: Second-order factor						Global (academic) self-concept ^a : Composite score			
	T1			T2			T1		T2	
	<i>M</i>	$\hat{\sigma}^2$	R^{2b} (range)	<i>M</i>	$\hat{\sigma}^2$	R^{2b} (range)	<i>M</i>	$\hat{\sigma}^2$	<i>M</i>	$\hat{\sigma}^2$
Study 1: BIJU										
M, G	2.09	0.07	.194 (.176 - .212)	2.10	0.11	.224 (.203 - .245)	2.08	0.22	2.11	0.30
M, G, E	2.06	0.07	.187 (.130 - .235)	2.07	0.11	.219 (.172 - .264)	2.07	0.18	2.06	0.23
M, G, E, B	2.00	0.07	.188 (.105 - .241)	2.04	0.11	.230 (.140 - .316)	2.01	0.16	2.02	0.20
M, G, E, B, P	2.02	0.11	.265 (.125 - .393)	2.09	0.13	.273 (.136 - .422)	2.04	0.17	2.07	0.20
S, A	2.28	0.18	.618 (.516 - .729)	2.17	0.23	.765 (.689 - .785)	2.29	0.23	2.16	0.26
S, A, Ap	2.28	0.14	.615 (.571 - .664)	2.20	0.17	.729 (.750 - .779)	2.28	0.17	2.20	0.20
All	2.13	0.08	.302 (.114 - .713)	2.11	0.09	.332 (.119 - .756)	2.13	0.12	2.12	0.14
Study 2: TRAIN										
M, G	2.97	0.07	.261 (.166 - .355)	2.88	0.06	.224 (.096 - .352)	3.00	0.18	2.83	0.20
M, G, E	3.01	0.09	.312 (.236 - .387)	2.87	0.08	.265 (.157 - .454)	3.03	0.16	2.85	0.17
S, A	2.97	0.26	.657 (.610 - .703)	3.04	0.23	.543 (.469 - .617)	3.03	0.33	3.03	0.33
All	3.00	0.13	.379 (.181 - .580)	2.95	0.10	.277 (.100 - .424)	3.03	0.16	2.92	0.15
Study 3: TOSCA-10										
M, V	2.91	-0.12	-	2.87	-0.09	-	2.91	0.15	2.90	0.18
M, V, E			No convergence				2.91	0.15	2.92	0.18
M, V, E, Ec	2.84	0.03	.038 ^c	2.82	0.03	.030 ^b	2.83	0.12	2.87	0.19

			(.013 - .057)				(.006 - .044)			
M, V, E, Ec, T	2.80	0.10	.011 ^c (.003 - .015)	2.79	0.10	.011 ^b (.002 - .017)	2.79	0.10	2.83	0.15

Note. $N_{\text{Study 1}} = 8,063$, $N_{\text{Study 2}} = 3,081$, $N_{\text{Study 3}} = 2,106$. M = Math, G = German, E = English, B = Biology, P = Physics, S = Social, A = Assertiveness, Ap = Appearance, V = Verbal, Ec = Economic, T = Technical.

^a The definition of the composite score is fundamentally determined by the selection of domain-specific self-concepts.

^b The average R^2 refers to the proportion of variance explained by the second-order factor in the first-order factors averaged across all first-order factors.

^c For some of the first-order factors, the explained variance could not be computed.

Table 6

Raw Rank-Order Stabilities and Correlations (and Covariances) of the Second-Order Factor and the Composite Score with Self-Esteem and Enjoyment of School in Studies 1 and 2

Set of self-concepts	Global self-concept: Second-order factor					Global self-concept ^a : Composite score				
	T1		T2		T1 with T2	T1		T2		T1 with T2
	<i>r(cov)</i> GSC, SE	<i>r(cov)</i> GSC, ES	<i>r(cov)</i> GSC, SE	<i>r(cov)</i> GSC, ES	<i>r(cov)</i> GSC T1, GSC T2	<i>r(cov)</i> GSC, SE	<i>r(cov)</i> GSC, ES	<i>r(cov)</i> GSC, SE	<i>r(cov)</i> GSC, ES	<i>r(cov)</i> GSC T1, GSC T2
Study 1: BIJU										
AC2: M, G	.74 (.12)	.52 (.09)	.78 (.17)	.47 (.08)	.56 (.05)	.42 (.12)	.29 (.09)	.47 (.17)	.29 (.08)	.50 (.13)
AC3: M, G, E	.74 (.12)	.50 (.09)	.76 (.17)	.47 (.08)	.65 (.06)	.49 (.13)	.33 (.09)	.52 (.17)	.33 (.08)	.57 (.12)
AC4: M, G, E, B	.67 (.11)	.44 (.07)	.71 (.16)	.43 (.07)	.70 (.06)	.50 (.12)	.33 (.08)	.55 (.17)	.34 (.08)	.57 (.10)
AC5: M, G, E, B, P	.56 (.12)	.34 (.07)	.63 (.15)	.38 (.07)	.68 (.08)	.49 (.13)	.32 (.08)	.55 (.16)	.34 (.08)	.59 (.11)
NAC2: S, A	.92 (.24)	.34 (.09)	.52 (.14)	.20 (.04)	.54 (.11)	.80 (.24)	.29 (.09)	.48 (.16)	.18 (.05)	.53 (.13)
NAC3: S, A, Ap	1.03(.24)	.31 (.07)	.55 (.16)	.21 (.05)	.50 (.08)	.91 (.23)	.29 (.08)	.51 (.15)	.20 (.04)	.52 (.10)
All	1.01(.18)	.33 (.07)	.66 (.13)	.27 (.05)	.56 (.05)	.77 (.17)	.36 (.08)	.63 (.16)	.34 (.06)	.59 (.08)
Study 2: TRAIN										
AC2: M, G	.61 (.13)	.79 (.13)	.64 (.12)	.77 (.11)	.60 (.04)	.39 (.13)	.46 (.12)	.37 (.13)	.38 (.10)	.45 (.09)
AC3: M, G, E	.50 (.12)	.60 (.11)	.52 (.11)	.57 (.10)	.75 (.06)	.38 (.12)	.44 (.11)	.38 (.12)	.38 (.09)	.49 (.08)
NAC2: S, A	.41 (.17)	.21 (.07)	.50 (.18)	.19 (.05)	.50 (.12)	.35 (.16)	.17 (.06)	.41 (.18)	.15 (.05)	.39 (.13)
All	.45 (.13)	.32 (.07)	.58 (.14)	.34 (.06)	.52 (.06)	.42 (.14)	.35 (.09)	.48 (.14)	.33 (.08)	.47 (.07)

Note. $N_{\text{Study 1}} = 8,063$, $N_{\text{Study 2}} = 3,081$. AC = Academic self-concept, NAC = Nonacademic self-concept, M = Math, G = German, E = English, B = Biology, P = Physics, S = Social, A = Assertiveness, Ap = Appearance, GSC = Global self-concept, SE = Self-esteem, ES = Enjoyment of school.

^a The definition of the composite score is fundamentally determined by the selection of domain-specific self-concepts.

Table 7

Raw Rank-Order Stabilities and Correlations (and Covariances) of the Second-Order Factor and the Composite Score with Academic Outcomes in Study 3

	Global academic self-concept: Second-order factor							Global academic self-concept ^a : Composite score						
	T1			T2			T1 with T2	T1			T2			T1 with T2
	<i>r(cov)</i>	<i>r(cov)</i>	<i>r(cov)</i>	<i>r(cov)</i>	<i>r(cov)</i>	<i>r(cov)</i>	<i>r(cov)</i>	<i>r(cov)</i>	<i>r(cov)</i>	<i>r(cov)</i>	<i>r(cov)</i>	<i>r(cov)</i>	<i>r(cov)</i>	<i>r(cov)</i>
	GSC,Ach	GSC,GPA	GSC,Tra	GSC,Ach	GSC,GPA	GSC,Tra	GSC T1, GSC T2	GSC,Ach	GSC,GPA	GSC,Tra	GSC,Ach	GSC,GPA	GSC,Tra	GSC T1, GSC T2
M, V	- (.06)	- (-.10)	- (.06)	- (.05)	- (-.06)	- (.02)	- (-.11)	.37 (.07)	-.52 (-.13)	.39 (.08)	.32 (.07)	-.31 (-.08)	.12 (.03)	.68 (.11)
M, V, E	No convergence							.32 (.06)	-.42 (-.10)	.36 (.07)	.34 (.07)	-.28 (-.07)	.14 (.03)	.68 (.11)
M, V, E, Ec	.28 (.03)	-.40 (-.05)	.27 (.03)	.25 (.02)	-.32 (-.03)	.15 (.01)	.91 ^b (.03)	.33 (.06)	-.40 (-.09)	.34 (.06)	.31 (.07)	-.28 (-.08)	.16 (.03)	.64 (.10)
M, V, E, Ec, T	.16 (.02)	-.25 (-.05)	.19 (.03)	.15 (.02)	-.19 (-.04)	.10 (.02)	.91 ^b (.09)	.34 (.05)	-.30 (-.06)	.22 (.04)	.33 (.06)	-.22 (-.05)	.10 (.02)	.66 (.08)

Note. $N_{\text{Study 3}} = 2,106$. M = Math, V = Verbal, E = English, Ec = Economic, T = Technical, GSC = Global academic self-concept, Ach = Average achievement score, GPA = grade point average, Tra = Transition after grade 10.

^a The definition of the composite score is fundamentally determined by the selection of domain-specific self-concepts.

^b This stability most likely represents math self-concept only because the second-order factor has a large loading on math self-concept and small or negative loadings on the other self-concepts. At the same time, the residual variances and the uniqueness (correlations of the residual variances) of math self-concept are negative.

(a)

(b)

(c)

Figure 1. Three representation of the structure of self-concept: (a) second-order factor based on the Shavelson model; (b) Marsh/Shavelson model; (c) Nested Marsh/Shavelson model.

Figure 2. Simplified representation of the present longitudinal second order factor model. GSC = Global self-concept. Correlated uniquenesses are not displayed. Bold lines represent research questions.

Figure 3. Simplified representation of the present longitudinal model-based composite score model. GSC = Global self-concept^a. Correlated uniquenesses are not displayed. Bold lines represent research questions.

^a The definition of the composite score is fundamentally determined by the selection of domain-specific self-concepts.

Appendix

Table A1

Fit Indices for the Longitudinal Models Tested in the BIJU Study

	χ^2	<i>df</i>	SF	CFI	TLI	RMSEA	SRMR	Warning
Correlated first-order factors	9581.04	2328	1.205	0.945	0.938	0.022	0.033	No
Latent composite score								
LCS All	9581.03	2328	1.205	0.945	0.938	0.022	0.033	No
LCS AC5	9581.03	2328	1.205	0.945	0.938	0.022	0.033	No
LCS AC4	9581.03	2328	1.205	0.945	0.938	0.022	0.033	No
LCS AC3	9581.03	2328	1.205	0.945	0.938	0.022	0.033	No
LCS AC2	9581.03	2328	1.205	0.945	0.938	0.022	0.033	No
LCS NAC3	9581.03	2328	1.205	0.945	0.938	0.022	0.033	No
LCS NAC2	9581.03	2328	1.205	0.945	0.938	0.022	0.033	No
Latent composite score + external criteria								
LCS All + Ex	12838.99	3344	1.195	0.937	0.930	0.021	0.034	No
LCS AC5 + Ex	12838.99	3344	1.195	0.937	0.930	0.021	0.034	No
LCS AC4 + Ex	12838.99	3344	1.195	0.937	0.930	0.021	0.034	No
LCS AC3 + Ex	12838.99	3344	1.195	0.937	0.930	0.021	0.034	No
LCS AC2 + Ex	12838.99	3344	1.195	0.937	0.930	0.021	0.034	No
LCS NAC3 + Ex	12838.99	3344	1.195	0.937	0.930	0.021	0.034	No
LCS NAC2 + Ex	12838.99	3344	1.195	0.937	0.930	0.021	0.034	No
Second-order factor								
SOF All	12775.12	2437	1.208	0.921	0.915	0.025	0.066	No
SOF AC5	10866.98	2416	1.207	0.935	0.903	0.023	0.046	No
SOF AC4	10733.98	2401	1.207	0.936	0.931	0.023	0.044	No
SOF AC3	10630.38	2382	1.206	0.937	0.931	0.023	0.041	No
SOF AC2	10591.85	2360	1.207	0.937	0.930	0.023	0.040	No
SOF NAC3	10372.55	2382	1.205	0.939	0.933	0.022	0.037	No
SOF NAC2	10133.87	2360	1.205	0.941	0.934	0.022	0.035	No

Second-order factor + external criteria

SOF All + Ex	16807.30	3509	1.197	0.911	0.906	0.024	0.062	Yes (2 & 3)
SOF AC5 + Ex	14394.25	3464	1.197	0.927	0.922	0.022	0.044	Yes (1)
SOF AC4 + Ex	14138.99	3441	1.197	0.929	0.923	0.021	0.042	Yes (2 & 3)
SOF AC3 + Ex	13960.16	3414	1.196	0.930	0.923	0.021	0.040	Yes (2)
SOF AC2 + Ex	13876.83	3384	1.196	0.930	0.923	0.021	0.038	Yes (2)
SOF NAC3 + Ex	15041.34	3420	1.195	0.923	0.916	0.022	0.038	Yes (2 & 3)
SOF NAC2 + Ex	13420.54	3384	1.196	0.933	0.926	0.021	0.035	Yes (2)

Note. $N = 8,063$. Results based on the MLR estimator (Muthén, & Muthén, 1998-2017); SF = Scaling Factor; CFI = Comparative Fit Index; TLI = Tucker Lewis Index; RMSEA = Root Mean Square Error of Approximation; SRMR = Standardized Root Mean Square Residual. Given that the RMSEA and CFI values are not estimated correctly when the MLR estimator is used, all RMSEA and CFI values were additionally adjusted in accordance with Brosseau-Liard et al. (2012) and Brosseau-Liard and Savalei (2014).

Estimation warnings in Mplus

- 1: “The first-order derivative product matrix is nonpositive definite; standard errors might not be trustworthy.” This warning most likely occurred because there were more parameters than there were clusters.
- 2: “The latent variable covariance matrix is not positive definite.” This warning most likely occurred because a latent variable had a negative (residual) variance, there was a correlation greater than or equal to 1 between two latent variables, or there was a linear dependency among more than two latent variables.
- 3: “The residual covariance matrix is not positive definite.” This warning most likely occurred because an observed variable had a negative (residual) variance, there was a correlation greater than or equal to 1 between two observed variables, or there was a linear dependency among more than two observed variables.

Table A2

Fit Indices for the Longitudinal Models Tested in the TRAIN Study

	χ^2	<i>df</i>	SF	CFI	TLI	RMSEA	SRMR	Warning
Correlated first-order factors	1702.73	540	1.132	0.954	0.935	0.028	0.046	Yes (1)
Latent composite score								
LCS All	1702.73	540	1.132	0.954	0.935	0.028	0.046	Yes (1)
LCS AC3	1702.73	540	1.132	0.954	0.935	0.028	0.046	Yes (1)
LCS AC2	1702.73	540	1.132	0.954	0.935	0.028	0.046	Yes (1)
LCS NAC2	1702.73	540	1.132	0.954	0.935	0.028	0.046	Yes (1)
Latent composite score + external criteria								
LCS All + Ex	4458.74	1216	1.125	0.907	0.886	0.031	0.048	No
LCS AC3 + Ex	4458.74	1216	1.125	0.907	0.886	0.031	0.048	No
LCS AC2 + Ex	4458.74	1216	1.125	0.907	0.886	0.031	0.048	No
LCS NAC2 + Ex	4458.74	1216	1.125	0.907	0.886	0.031	0.048	No
Second-order factor								
SO All	2286.69	577	1.138	0.931	0.910	0.033	0.058	Yes (1)
SO AC3	1993.78	567	1.135	0.943	0.924	0.031	0.056	Yes (1)
SO AC2	2069.43	557	1.133	0.940	0.918	0.032	0.057	Yes (1)
SO NAC2	2001.99	557	1.134	0.942	0.921	0.031	0.054	Yes (1)
Second-order factor + external criteria								
SOF All + Ex	5341.36	1285	1.1278	0.884	0.865	0.034	0.062	Yes (1)
SOF AC3 + Ex	4966.64	1260	1.1249	0.894	0.874	0.033	0.057	Yes (1 & 2)
SOF AC2 + Ex	4863.95	1241	1.1254	0.896	0.875	0.033	0.055	Yes (2)
SOF NAC2 + Ex	4787.45	1242	1.1272	0.898	0.878	0.032	0.052	No

Note. $N = 3,081$ for models with external criteria and $N = 3,033$ for models without external criteria. Results based on the MLR estimator (Muthén, & Muthén, 1998-2017); SF = Scaling Factor; CFI = Comparative Fit Index; TLI = Tucker Lewis Index; RMSEA = Root Mean Square Error of Approximation; SRMR = Standardized Root Mean Square Residual. Given that the RMSEA and CFI values are not estimated correctly when the MLR estimator is used, all RMSEA and CFI values were additionally adjusted in accordance with Brosseau-Liard et al. (2012) and Brosseau-Liard and Savalei (2014).

Estimation warnings in Mplus

- 1: "The first-order derivative product matrix is nonpositive definite; standard errors might not be trustworthy." This warning most likely occurred because there were more parameters than there were clusters.
- 2: "The latent variable covariance matrix is not positive definite." This warning most likely occurred because a latent variable had a negative (residual) variance, there was a correlation greater than or equal to 1 between two latent variables, or there was a linear dependency among more than two latent variables.
- 3: "The residual covariance matrix is not positive definite." This warning most likely occurred because an observed variable had a negative (residual) variance, there was a correlation greater than or equal to 1 between two observed variables, or there was a linear dependency among more than two observed variables.

Table A3

Fit Indices for the Longitudinal Models Tested in the TOSCA-10 Study

	χ^2	df	SF	CFI	TLI	RMSEA	SRMR	Warning
Correlated first-order factors	3439.16	941	1.089	0.939	0.922	0.037	0.048	Yes (1)
Latent composite score								
LCS All	3439.16	941	1.089	0.939	0.922	0.037	0.048	Yes (1)
LCS AC4	3439.16	941	1.089	0.939	0.922	0.037	0.048	Yes (1)
LCS AC3	3439.16	941	1.089	0.939	0.922	0.037	0.048	Yes (1)
LCS AC2	3439.16	941	1.089	0.939	0.922	0.037	0.048	Yes (1)
Latent composite score + external criteria								
LCS All + Ex	3798.11	1093	1.077	0.943	0.926	0.036	0.046	No
LCS AC4 + Ex	3798.11	1093	1.077	0.943	0.926	0.036	0.046	No
LCS AC3 + Ex	3798.11	1093	1.077	0.943	0.926	0.036	0.046	No
LCS AC2 + Ex	3798.11	1093	1.077	0.943	0.926	0.036	0.046	No
Second-order factor								
SOF All	3805.77	978	1.091	0.931	0.915	0.039	0.086	Yes (1)
SOF AC4	3783.21	975	1.091	0.931	0.915	0.039	0.085	Yes (1)
SOF AC3	3720.98	968	1.091	0.933	0.916	0.038	0.084	Yes (1)
SOF AC2	4120.40	958	1.091	0.923	0.903	0.041	0.122	Yes (1 & 2)
Second-order factor + external criteria								
SOF All + Ex	5123.64	1162	1.077	0.916	0.898	0.042	0.110	Yes (1 & 2)
SOF AC4 + Ex	5001.96	1151	1.076	0.918	0.900	0.041	0.102	Yes (1 & 2)
SOF AC3 + Ex			No convergence					--
SOF AC2 + Ex	4875.48	1118	1.079	0.920	0.899	0.042	0.115	Yes (2)

Note. $N = 2,106$ for models with external criteria and $N = 2,098$ for models without external criteria. Results based on the MLR estimator (Muthén, & Muthén, 1998-2017); SF = Scaling Factor; CFI = Comparative Fit Index; TLI = Tucker Lewis Index; RMSEA = Root Mean Square Error of Approximation; SRMR = Standardized Root Mean Square Residual. Given that the RMSEA and CFI values are not estimated correctly when the MLR estimator is used, all RMSEA and CFI values were additionally adjusted in accordance with Brosseau-Liard et al. (2012) and Brosseau-Liard and Savalei (2014).

Estimation warnings in Mplus

- 1: “The first-order derivative product matrix is nonpositive definite; standard errors might not be trustworthy.” This warning most likely occurred because there were more parameters than there were clusters.
- 2: “The latent variable covariance matrix is not positive definite.” This warning most likely occurred because a latent variable had a negative (residual) variance, there was a correlation greater than or equal to 1 between two latent variables, or there was a linear dependency among more than two latent variables.
- 3: “The residual covariance matrix is not positive definite.” This warning most likely occurred because an observed variable had a negative (residual) variance, there was a correlation greater than or equal to 1 between two observed variables, or there was a linear dependency among more than two observed variables.

Appendix B: Results From the Nested Marsh/Shavelson Model in Studies 1 and 2¹

Along with the theoretical and analytical models on the hierarchy of self-concepts analyzed in the present manuscript, there has been another influential model in this vivid research field, namely, the Nested Marsh/Shavelson model, which we also mentioned in the theoretical background (see Figure 1, Part c; Brunner et al., 2010). The Nested Marsh/Shavelson model was an important further development in research on the hierarchy of self-concept as it could address many of the problems that occurred in the Shavelson model (single higher order factor) and the Marsh/Shavelson model (separate factors for math and verbal self-concept) by accounting for both the generality and the correlations between specific factors. At the same time, and in contrast to all other models, this model placed higher demands on the data set because it required a global measure that defined the global factor. Thus, the Nested Marsh/Shavelson model was implemented through a correlated trait correlated method minus one (CTC M-1) model (Eid et al., 2003). The crucial theoretical and analytical decision that needed to be made before implementing this model was the selection of a global measure of self-concept that defined the global factor.

The Nested Marsh/Shavelson model was proposed and has primarily been applied in the field of academic self-concepts (although it might not be restricted to the latter) by drawing on a measure of (global) academic self-concept (Brunner et al., 2010). Yet, when interested in global self-concept, such as in most of our manuscript, it is unclear how this model can be implemented, and which global measure is an appropriate anchor for global self-concept. Even though the application of this model to global self-concept has not garnered much theoretical or empirical interest so far, initial considerations (Arens et al., 2020; Morin et al., 2016) have suggested that

such a model could be applied to global self-concept. One possibility for applying this model to global self-concept is to draw on measures of global self-esteem (e.g., Rosenberg, 1965) as the global measure that defines the global factor. In the present manuscript, we used self-esteem measures as external criteria in order to evaluate global self-concept on the basis of the second-order factor and the composite score model. Yet, for the sake of providing additional insights into the application of the Nested Marsh/Shavelson model, we used the self-esteem measures as global measures for defining the global factor as part of the CTC-M-1 model. By doing so, the global factor was identified by a nonarbitrary model identification (Little et al., 2006) across all self-esteem items. All data analysis scripts of these analyses are available for review on the Open Science Framework at the following address:

https://osf.io/63nk8/?view_only=0e61f97dda0b48d4bd4d10eb463a9627 (the project will be publicly available after the review process has been completed).

Table B1 presents the means and variances of the global factor, its correlations with enjoyment of school, and its stabilities from the CTC M-1 models in Studies 1 and 2. First, the model fit as well as the means and variances of the global factor in the CTC M-1 model were not directly comparable to the model fit or to the means and variances of global self-concept in the second-order factor model or the composite score model because the models were not comparable (i.e., the CTC M-1 model includes the additional measure of global self-esteem). Second, with regard to the correlations with enjoyment of school as well as the stabilities, the results for the CTC M-1 model indicated that these coefficients were less affected by the composition and set of self-concepts compared with the second-order factor model and the composite score model (see Table 6). One reason for this pattern might be that the CTC M-1 model is to a large extent determined by the self-esteem items. Thus, the inclusion of additional domain-specific self-concepts was less influential than in the other two models. Third, when

comparing the sizes of the coefficients (i.e., correlations and stabilities) from the CTC M-1 model with the second-order factor model and the composite score model (see Table 6), there was no clear advantage of either of these models in terms of the sizes of the standardized coefficients. Thus, in Study 1, the coefficients were higher in the CTC M-1 model, yet, in Study 2, it was largely the opposite, and the coefficients were higher in the composite score model.

Overall, the results from the CTC M-1 model indicated a stable pattern of results across different compositions of domain-specific self-concepts. There were no clear advantages in terms of the sizes of the correlations and stabilities compared with the other models. When interpreting the results from the CTC M-1 model, we have to take into account the strong dependency of this model on the global measure drawn to anchor the global factor. By contrast, the second-order factor model as well as the composite score model did not require such a measure. Instead, they were explicitly aimed at inferring global self-concept. Whereas the comparison of such modeling approaches (modeling global self-concept) was the core of this manuscript, the CTC M-1 model was shown to be another fruitful approach for modeling the hierarchy of self-concepts when (a) a global measure is available and (b) the global factors are theoretically intended to be anchored by this global measure.

¹ We were not able to apply the Nested Marsh/Shavelson model in Study 3 because no measure of global academic self-concept was available.

Table B1

Means and Variances of Global Self-Concept and Raw Rank-Order Stabilities and Correlations (and Covariances) with Enjoyment of School of the CTC M-1 Model in Studies 1 and 2

Set of self-concepts	T1			T2			T1 with T2
	M	$\hat{\sigma}^2$	r(cov) GSC, ES	M	$\hat{\sigma}^2$	r(cov) GSC, ES	r (cov) GSC T ₁ , GSC T ₂
Study 1: BIJU							
AC2: M, G	2.13	0.25	.41 (.13)	1.98	0.37	.39 (.12)	.64 (.19)
AC3: M, G, E	2.13	0.25	.41 (.13)	1.98	0.37	.39 (.12)	.64 (.19)
AC4: M, G, E, B	2.13	0.25	.41 (.13)	1.98	0.37	.39 (.12)	.65 (.20)
AC5: M, G, E, B, P	2.13	0.25	.40 (.13)	1.98	0.36	.39 (.12)	.66 (.20)
NAC2: S, A	1.62	0.72	.55 (.33)	1.43	0.66	.52 (.24)	.70 (.48)
NAC3: S, A, Ap	1.81	0.56	.50 (.26)	1.38	0.71	.55 (.26)	.67 (.42)
All	2.13	0.30	.40 (.14)	1.98	0.33	.39 (.11)	.62 (.20)
Study 2: TRAIN							
AC2: M, G	3.48	0.64	.40 (.20)	3.49	0.57	.34 (.15)	.37 (.22)
AC3: M, G, E	3.48	0.63	.41 (.21)	3.47	0.57	.34 (.15)	.37 (.22)
NAC2: S, A	3.47	0.62	.40 (.20)	3.49	0.57	.33 (.15)	.37 (.22)
All	3.47	0.63	.41 (.21)	3.49	0.57	.34 (.15)	.39 (.24)

Note. $N_{\text{Study 1}} = 8,063$, $N_{\text{Study 2}} = 3,081$. AC = Academic self-concept, NAC = Nonacademic self-concept, M = Math, G = German, E = English, B = Biology, P = Physics, S = Social, A = Assertiveness, Ap = Appearance, GSC = Global self-concept, ES = Enjoyment of school.