**Measurement Invariance of the Intelligence and Development Scales–2
Across Language Versions, Gender, and Age**

Silvia Grieder^{1*}, Linda Visser^{2*}, Marieke E. Timmerman³, and Alexander Grob¹

¹ Department of Psychology, University of Basel

² Department of Education and Human Development, DIPF | Leibniz Institute for Research and
Information in Education

³ Heymans Institute for Psychological Research, University of Groningen

Author Note

Silvia Grieder <https://orcid.org/0000-0002-0118-7722>

Linda Visser <https://orcid.org/0000-0002-4091-7054>

Marieke E. Timmerman <https://orcid.org/0000-0003-1579-6964>

Alexander Grob <https://orcid.org/0000-0002-0715-4139>

* co-first author

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Correspondence concerning this article should be addressed to Linda Visser, Department of Education and Human Development, DIPF | Leibniz Institute for Research and Information in Education, Rostocker Straße 6, 60323 Frankfurt am Main, Germany. E-mail: l.visser@dipf.de.

Abstract

We examined the factor structure and measurement invariance of the intelligence and basic skills domains of the Intelligence and Development Scales–2 (IDS-2) with the Dutch ($N = 1,665$) and German ($N = 1,672$) standardization samples. First, we tested five competing models using confirmatory factor analysis (CFA) on the Dutch data: two empirically based, derived earlier from the German data, and three theoretically based (IDS-2 and two Cattell–Horn–Carroll-based). Subsequently, we evaluated the measurement invariance of the final model across the Dutch and German versions and gender using multiple-group CFA and across age using local structural equation modeling. A second-order model with six first-order factors best represented the Dutch IDS-2 structure. Five IDS-2 factors were confirmed, but Visual Processing and Abstract Reasoning, and the intelligence and basic skills domains were not separable. This model displayed full invariance across the language versions and was largely invariant across gender and age (7 - 20 years). Thus, scores derived according to this model are comparable across these language versions, gender, and age. The strong general intelligence factor and weak broad ability factors ask for precaution when basing clinical interpretation on the broad ability factors.

Keywords: Intelligence and Development Scales–2, structural validity, confirmatory factor analysis, measurement invariance, local structural equation modeling

Measurement Invariance of the Intelligence and Development Scales–2

Across Language Versions, Gender, and Age

Validation of a test is crucial to determine its ability to measure the intended constructs. If the interpretation of the test's scores is based on a hypothesized internal structure, evidence concerning this structure should be provided as part of the validation process, for example using factor analysis (American Educational Research Association et al., 2014). There are two approaches to achieve this structural validation. The first is a data-driven procedure in which an exploratory factor analysis (EFA) is conducted first, followed by a confirmatory factor analysis (CFA) to test the factor structure found on a new sample (e.g., Brown, 2015; Reise, 2012). The second is theory-driven and concerns evaluating various theoretically plausible models. Once the most useful factor structure has been determined with a large, representative sample, measurement invariance should be tested across subgroups differing in important demographic characteristics such as native language, ethnicity, gender, and age. If this is demonstrated, the factor structure and thus the score interpretation will be consistent across these groups. In the present study, we adopted the procedure outlined above for the structural validation of the Intelligence and Development Scales–2 (IDS-2; Grob & Hagmann-von Arx, 2018). More specifically, based on the results of a previous study in which an EFA was conducted (AUTHORS, 2020), the current study deploys CFA to evaluate both the EFA-based (data-driven) and multiple theoretical models and subsequently tests measurement invariance across language versions, gender, and age.

The IDS-2

The IDS-2 assesses cognitive and developmental functions in 5- to 20-year-olds. Based on its original German version, international adaptations and standardizations of 12 additional language versions have been or are being developed. Results of the present study

are based on the German (Grob & Hagmann-von Arx, 2018) and Dutch (Grob et al., 2018) versions.

The intelligence and basic skills domains of the IDS-2 are theoretically developed from the Cattell–Horn–Carroll (CHC) model (McGrew, 1997; Schneider & McGrew, 2018), which was introduced as an integration of Cattell and Horn’s fluid–crystallized (Gf-Gc; Cattell, 1941; Horn, 1991) and Carroll’s (1993) three-stratum model, although it might be more appropriately seen as an extension of the Gf-Gc model (Canivez & Youngstrom, 2019). It postulates a higher-order intelligence structure with over 80 narrow abilities on Stratum I and, in its most recent version (Schneider & McGrew, 2018), at least 14 broad abilities on Stratum II. Although general intelligence is most often included on Stratum III (consistent with Carroll’s model), the CHC authors themselves are skeptical about it being a real entity (Schneider & McGrew, 2018). The CHC model has been widely used as a comprehensive framework in intelligence research and test construction, but it has also been criticized, especially for its de-emphasis of general intelligence in favor of broad abilities (e.g., Canivez & Youngstrom, 2019; Cucina & Howardson, 2017).

The IDS-2 intelligence domain includes 14 subtests that enable the assessment of seven broad abilities largely corresponding to the CHC broad abilities, see Table S1. The IDS-2 factors deviate in two ways from current CHC broad abilities. First, short-term memory is separated into an auditory and a visual–spatial component, corresponding to the narrow abilities of Working Memory Capacity in the CHC model and to the different slave systems according to the working memory model by Baddeley (2003). Second, long-term storage and retrieval is combined, corresponding to the way this broad ability was defined by the time the IDS-2 was developed. General intelligence is measured with a full-scale IQ consisting of all 14 intelligence subtests. The basic skills subtests Logical–Mathematical Reasoning (LMR), Reading, and Spelling can also be integrated in the CHC framework:

LMR contains aspects of Fluid Reasoning and Quantitative Knowledge; Reading and Spelling measure Reading and Writing. The reason these subtests were not included in the intelligence domain is their dependence on prior knowledge (Bodovski & Farkas, 2007; Tarchi, 2010). In the present study, we focused on all 14 intelligence subtests and the three basic skills subtests LMR, Reading, and Spelling.

Factor Structure

In previous research, the major intelligence theories have mostly been represented by higher-order models, that is, models where the subtests are indirectly linked to the general intelligence factor through the broad ability factors. More recently, the bifactor or direct hierarchical model (Reise, 2012) has regained popularity. Here, the subtests are directly linked to the general intelligence factor and the broad ability factors, and the broad ability factors are orthogonal to each other and to the general intelligence factor. The bifactor model's revival is due to several advantages of bifactor models over higher-order models. One of them is the more intuitive and, arguably, theoretically more plausible conceptualization of general intelligence as a breadth instead of a superordinate factor (e.g., Beaujean, 2015; Gignac, 2008). Further, it is well suited to comparing the relative importance of the general intelligence factor and the broad ability factors through variance partitioning, for example, with model-based reliability estimates such as McDonald's omegas (McDonald, 1985, 1999). Eid and colleagues (2017) have introduced a variant of the bifactor model called the bifactor(S-1) model in which one specific factor is omitted. Applied to intelligence theory this implies that "the g factor represents individual differences on the facet that is theoretically selected as the reference facet" (Eid et al., 2018, p. 12) rather than a general factor representing all facets included in an intelligence test.

Nevertheless, if a higher-order model were to fit the population, then it would be preferred over a bifactor model, because of parsimony, and thus more precise estimation. In

empirical practice, the true population model is unknown, and one needs to rely on fit measures that balance model fit and model complexity. In the present study, we therefore tested higher-order, bifactor, as well as bifactor (S-1) versions of all postulated models.

The structural validity evidence included in the German and Dutch IDS-2 manuals is restricted to the intelligence domain (Grob et al., 2018; Grob & Hagmann-von Arx, 2018). For both the German and Dutch versions, CFAs with the standardization samples revealed that the higher-order theoretical model—with all 14 subtests on Stratum I, seven broad abilities on Stratum II, and general intelligence on Stratum III—displayed good fit.

AUTHORS (2020) examined the factor structure for the German IDS-2 intelligence and basic skills domains with EFA with principal axis factoring and promax rotation. They found two plausible models that both resemble the theoretical IDS-2 structure for intelligence, but with Visual Processing and Abstract Reasoning collapsed to one factor (Abstract Visual Reasoning) and an additional factor Reading and Writing. LMR showed a substantial loading on Abstract Visual Reasoning and the highest general intelligence factor loading in a Schmid–Leiman solution. In one model (*EFA-based SLM*, see Figure 1), Long-Term Memory and Verbal Reasoning collapsed to one Semantic Long-Term Memory factor. In the other model (*EFA-based VR_LM*), these two factors were still separate, but there was a cross-loading of Story Recall on Verbal Reasoning. This model was discarded because of Heywood cases (likely being a sign of underidentification), but was otherwise plausible and is worth reexamination.

The EFA results thus partly supported the IDS-2 model. A separation of intelligence and basic skills domains did not hold empirically, because there was a strong general intelligence factor encompassing all subtests. In addition, the explained variances and McDonald's omegas (McDonald, 1985, 1999) revealed a strong general intelligence factor and weak broad ability factors.

Measurement Invariance

The IDS-2 manuals report results from multiple-group CFAs (MGCFAs; e.g., Steenkamp & Baumgartner, 1998) for gender and age groups, using the theoretical IDS-2 model. The results supported full invariance for the Dutch IDS-2, partial scalar invariance for the German IDS-2 across gender, and full invariance across the age groups of 5–8, 9–12, and 13–20 years for both versions (Grob et al., 2018; Grob & Hagmann-von Arx, 2018). IDS-2 intelligence scores can thus meaningfully be compared between children and adolescents of different gender and from different age groups. However, measurement invariance has not yet been examined across gender and age for the basic skills subtests, and not at all across language versions.

Present Study

We aimed to evaluate the factor structure of the IDS-2 intelligence and basic skills domains, considering five (theoretically and empirically founded) candidate models, using the data from the Dutch standardization sample, and to evaluate the measurement invariance of the instrument based on this factor structure in relation to language versions (German and Dutch), gender, and age. The research questions are as follows.

Research question (RQ) 1. Which model best represents the structure of the intelligence and basic skills domains for the Dutch IDS-2? Using CFA with the Dutch standardization sample, we tested a *g* model, with all subtests loading onto one general intelligence factor, the two aforementioned EFA-based models (*EFA-based SLM* and *EFA-based VR_LM*; AUTHORS, 2020), the IDS-2 model, and two operationalizations of the CHC model (*CHC w/o Gq* and *CHC w/ Gq* with LMR as an indicator of Fluid Reasoning and Quantitative Knowledge, respectively). For all models except the *g* model, we tested both higher-order (Figure 1), bifactor, and bifactor(S-1) (Figure S1) operationalizations. For a

detailed description, see the Supplement, section 1.1. We expected Model *EFA-based SLM* to fit best, given the results for the German IDS-2 (AUTHORS, 2020).

Based on the final model, are the intelligence and basic skills domains measurement invariant across:

RQ 2. the Dutch and German IDS-2 versions?

RQ 3. gender (females and males¹)?

RQ 4. age (7 to 20 years).

Based on the results reported in the manuals, which were based on the IDS-2 intelligence model, we expected to find at least partial scalar invariance across gender and full invariance across age.

Materials and Methods

Participants

Data from the standardization samples of the Dutch and German IDS-2 ($N = 1,665$ and $N = 1,672$, respectively) were used.

Dutch Sample

For the Dutch IDS-2, children were recruited via schools, organizations, personal contacts, and social media. We excluded a total of 204 participants younger than 7 years of age due to the minimum age of 7 years required for conducting the Reading and Spelling subtests, and another 38 because more than 50% of the subtest scores were missing, resulting in a final sample of 1,423 participants from the Netherlands. The mean age for this sample was 13.08 years ($SD = 3.98$, range: 7.00–21.89 years) and 52% were female. The Dutch standardization sample was aimed to be representative for the Dutch population of children and adolescents aged 5 to 20 years in terms of gender, ethnic background of the parents,

¹ We use the terms *females* and *males* to refer to persons self-identifying as girls and/or women and boys and/or men, respectively.

educational background of the mother, degree of urbanization, region, education type (for secondary school students), and common diagnoses. Although some statistically significant differences appeared in the sample proportions as compared to the population proportions (based on a z-test; see Table S2), the influence of the deviations on the test scores appeared negligible. We refer to the manual (Grob et al., 2018) for details.

German Sample

For the German IDS-2, participants were recruited via schools and psychosocial institutions for children and adolescents in Switzerland, Germany, and Austria. We excluded 254 participants younger than 7 years of age (again due to the minimum age of 7 years required for the Reading and Spelling subtests), and 13 participants because more than 50% of the subtest scores were missing. The final sample consisted of 1,405 participants from Switzerland ($n = 812$), Germany ($n = 517$), and Austria ($n = 76$). The mean age was 13.12 years ($SD = 3.90$, range: 7.01–20.98 years) and 51% were female. The subsamples for Switzerland, Germany, and Austria were aimed to be representative for the Swiss, German, and Austrian population of children and adolescents aged 5 to 20 years in terms of gender, bilingualism, educational background of the mother, education type, and common diagnoses. Again, some statistically significant differences appeared in the sample proportions as compared to the population proportions (based on a z-test; see Table S3). Differences between the test scores across the three samples were negligible (see manual for details; Grob & Hagmann-von Arx, 2018), meaning that the three samples can be combined.

Materials and Procedure

The IDS-2 is an individually administered test for 5- to 20-year-olds that enables the assessment of intelligence, executive functions, and (age-dependent) developmental functions (psychomotor skills, socioemotional competence, basic skills, and attitude toward work) with 30 subtests, of which 14 for intelligence and three for basic skills (see Table S1; for

descriptive statistics see Table S4) were considered in the present study. Administration time was between 3.5 and 4.5 hr, which, if necessary, was split into two sessions no more than 1 week apart. Children and adolescents (10- to 20-year-olds) and/or their parents (for 5- to 15-year-olds) provided written consent prior to testing. Parents or adolescents provided demographic information using a personally administered questionnaire at the beginning of the first session. Participants received a gift card of 10 to 30 euros, depending on the country. Ethical approval was obtained from the [BLINDED] (German sample). A statement on the exemption of an explicit ethical approval was obtained from the [BLINDED] (Dutch sample).

Statistical Analyses

All analyses were conducted in R using age-standardized subtest scores ($M = 10$, $SD = 3$). CFAs were conducted with the lavaan package, version 0.60–7 (Rosseel, 2012) using the full information maximum likelihood method. Indices of interpretive relevance were calculated with the EFAtools package, version 0.3.0 (Steiner & Grieder, 2020). Local Structural Equation Modeling (LSEM) was conducted with the Sirt package (Robitzsch, 2020).

Analysis Procedure

RQ 1. We tested the competing models listed in Figures 1 and S1 for the Dutch IDS-2. We call the best model (according to our model selection criteria introduced below) the *final model*.

RQ 2. Following Steenkamp and Baumgartner (1998), we first tested for equality between the Dutch and German IDS-2 covariance matrices using Box's M test (Box, 1949) and of mean vectors using Nel and Van der Merwe's procedure (1986). If equality was not supported, we tested measurement invariance across the Dutch and German IDS-2 using MGCFA for the final model. Herewith, we followed the sequence of model comparisons suggested in Chen et al. (2005; see Supplement for details). If configural invariance did hold,

we fitted the final model for the German IDS-2 as well. Otherwise, we fitted the models tested for RQ 1 also for the German IDS-2 to find the best fitting model for the German IDS-2 and proceeded from there.

RQ 3. We tested gender invariance for the final model(s) separately for the two IDS-2 versions. As for RQ 2, we tested for equality of covariance matrices and mean vectors; if these were not equal, we tested for invariance of the model parameters across gender.

RQ 4. We examined age invariance for the final model(s) separately for the two IDS-2 versions using LSEM (Hildebrandt et al., 2009; 2016; see Supplement for details). Here, LSEM is more realistic than MGCFA, because it accounts for the continuous nature of age by assuming a smooth relationship between age and possible deviations from measurement invariance.

For a detailed description of the measurement invariance analyses, see section 2 of the Supplement.

Model Identification

The models were standardized by fixing the variances of all latent variables to unity. For factors with only one indicator, we fixed the single indicator's residual variance to $(1 - \alpha) * SD^2$ (e.g., Brown, 2015, p. 139), where α is the indicator's (i.e., subtest's) reliability (Cronbach's alpha) and SD its SD in the sample. For bifactor models, loadings of factors with only two indicators were constrained to be equal to achieve identifiability.

Model Selection

We considered $CFI \geq .95$, $RMSEA \leq .06$, and standardized root mean square residual (SRMR) $\leq .08$ as indices of good fit (Hu & Bentler, 1999). We deemed fit to be acceptable if the SRMR and at least one of the two other fit indices met the cutoff criteria (Hu & Bentler, 1998, 1999). In addition, a model had to be free of local fit problems such as nonsignificant or near-unity factor loadings, inflated standard errors, or negative variances.

If the results of RQ 1 showed that more than one of the candidate models displayed good fit, the model with the lowest Akaike information criterion (AIC) was considered. Then, this model was compared to more parsimonious models (larger degrees of freedom) using the following delta fit criteria suggested by Chen (2007): $\Delta\text{CFI} < -.01$, $\Delta\text{RMSEA} < .015$, and $\Delta\text{SRMR} < .03$. If a more parsimonious model displayed no worsening in fit according to all these criteria, the parsimonious model was selected. For the MGCFA (RQ 2 and 3), we used the same criteria, except of using $\Delta\text{SRMR} < .01$ for invariance of intercepts and residuals (see Chen, 2007). The χ^2 and $\Delta\chi^2$ values were not interpreted because of their sensitivity to large sample sizes (Barrett, 2007).

McDonald's Omegas

We calculated McDonald's omegas (McDonald, 1985, 1999) for the final models of the three studies. Omegas partition a unit-weighted composite's true score variance into variance explained by the general factor (omega hierarchical, ω_h), and by the subscale factors (omega subscale, ω_s). The total true score variance is estimated with omega total (ω_t). For ω_h (full scale), a minimum of .50, with .75 being preferred, has been suggested as satisfactory (Reise et al., 2013). For ω_s (subscales), more recent research suggests the following empirically derived thresholds for interpretation: $< .20$ = small, $.20-.30$ = typical, $> .30$ = relatively large (Gignac & Kretzschmar, 2017). We calculated these indices either directly from a bifactor model, or from a Schmid–Leiman transformed higher-order model (Schmid & Leiman, 1957).

Results

RQ 1: Model Selection for the Dutch IDS-2

The fit for all tested models (Figures 1 and S1) for the Dutch IDS-2 is displayed in Table 1. Nine of the 16 evaluated models were discarded owing to unacceptable local (see Table S5) or global fit. Of the remaining models, *EFA-based VR_LM bifactor* had the lowest

AIC and was compared to the more parsimonious higher-order model *EFA-based VR_LM*, which had the second-best fit and higher degrees of freedom. The higher-order model *EFA-based VR_LM* met our delta fit criteria and we thus compared this model in turn with the more parsimonious higher-order model *EFA-based SLM*, which is the only model with even higher degrees of freedom and without local fit problems. Model *EFA-based SLM* did not meet our delta fit criteria. Thus, we selected the higher-order model *EFA-based VR_LM* as the final model for the Dutch IDS-2 (see Figure 2a).

RQ 2: Invariance Analyses Across the Dutch and German IDS-2 Versions

Neither the covariance matrices ($\chi^2(153) = 269.94, p < .001$) nor the mean vectors ($F(17, 2808) = 4.06, p < .001$) were equivalent. The MGCFAs with the final model identified for the Dutch IDS-2 revealed full invariance of all tested model parameters (i.e., first- and second-order loadings, intercepts, first-order factor means, residuals, and first-order factor disturbances) across the Dutch and German IDS-2 versions (see Table 2). Therefore, we fitted this model also on the German IDS-2 (see Figure 2b).

Omegas were similar across the two IDS-2 versions (see Figure 2). ω_h was above the threshold of .75 for the general intelligence composite. For both IDS-2 versions, ω_s was below .20 (i.e., small) for Abstract-Visual Reasoning, between .20 and .30 (i.e., typical) for Long-Term Memory, and above .30 (i.e., relatively large) for Perceptual Speed, Auditory- and Visual-Spatial Short-Term Memory. For both Reading and Writing and Verbal Reasoning, ω_s was small for the Dutch and typical for the German IDS-2.

RQ 3: Invariance across gender

We found no equivalence of covariance matrices and mean vectors, neither for the Dutch nor for the German IDS-2, Box's M test: $\chi^2(153) = 242.54, p < .001$ and $\chi^2(153) = 250.20, p < .001$, respectively; Nel and Van der Merwe's test: $F(17, 1389) = 11.29, p < .001$ and $F(17,$

1364) = 17.62, $p < .001$, respectively. We therefore conducted MGCFAs with the final model to further investigate gender invariance.

The first- and second-order loadings were invariant across gender for both IDS-2 versions, and thus metric invariance was supported (see Table S6). However, only partial scalar invariance was supported. For the Dutch IDS-2, the intercepts of Picture Recall and Shape Design had to be freed to achieve a nonsubstantial worsening in fit. Females scored higher in Picture Recall (estimated intercepts 10.93 vs. 9.77), and males scored higher in Shape Design (estimated intercepts 10.54 vs. 9.79). For the German IDS-2, the intercepts of Picture Recall and Spelling had to be freed, with females scoring higher in both subtests (estimated intercepts 11.04 vs. 9.72 and 10.74 vs. 9.50, respectively). The first-order factor means were again invariant for both IDS-2 versions. Finally, based on the partial scalar invariance, partial strict invariance was supported for both IDS-2 versions, with all residuals and first-order factor disturbances being invariant. Parameter estimates and omegas for females and males based on the configural invariance model are displayed in Figure S6.

Omeegas were similar across gender for both IDS-2 versions. ω_h was always above .75 for the general intelligence composite. ω_s was again relatively large for Processing Speed and Auditory Short-Term Memory, typical for Long-Term Memory, and small for Abstract-Visual Reasoning. ω_s for Visual-Spatial Short-Term Memory was relatively large for both genders for the German IDS-2 and for females for the Dutch IDS-2, but typical for males for the Dutch IDS-2. For Reading and Writing, ω_s was again small for the Dutch IDS-2 for both genders, while, for the German IDS-2, it was typical for males and relatively large for females. Finally, ω_s for Verbal Reasoning was small for males for the Dutch and for females for the German IDS-2, while it was typical for females for the Dutch and for males for the German IDS-2.

RQ 4: Age Invariance

We investigated age invariance in model fit, first- and second-order loadings, and residuals for the final model. Table S7 shows effective age and sample sizes at each focal age point. In the following, for simplicity, we refer to the focal age points as “age” (e.g., at age 7 years means at focal age point 7). For both IDS-2 versions, model fit in terms of CFI, RMSEA, and SRMR tended to become worse at older ages (see Figure 3). For the Dutch IDS-2, model fit was acceptable for ages 7 to 16 years, but no longer for ages 17 to 20 years. For the German IDS-2, fit was acceptable for ages 7 to 12 years, but no longer for ages 13 to 20 years.

For both IDS-2 versions, most first-order loadings were invariant, that is, there were no significant pointwise tests (see Figure S2). For the Dutch IDS-2, five of 18 first-order loadings had significant pointwise tests. The loading of Mixed Digit and Letter Span on Auditory Short-Term Memory was significantly lower at ages 7 to 10 years, and significantly higher at ages 15 to 19 years. The loadings of Naming Categories and Naming Opposites on Verbal Reasoning were significantly higher at ages 20 and 15 to 16 years, respectively. We found drops in the loadings of Parrots on Processing Speed at ages 12 and 13 years and of Rotated Shape Memory on Visual–Spatial Short-Term Memory at ages 7 and 8 years. For the German IDS-2, significant pointwise tests occurred for only one of 18 first-order loadings. The loading of Naming Categories on Verbal Reasoning was significantly lower at age 7 years and higher at ages 17 and 18 years. The second-order loadings were completely invariant for both IDS-2 versions (see Figure S3). Finally, for residuals, results from pointwise tests displayed the same pattern of significance as described for the first-order loadings above, but with the opposite direction of effects (see Figure S4).

Omegas varied somewhat across age for both IDS-2 versions (see Figure S5). ω_h was again above .75 for the general intelligence composite. For Abstract-Visual Reasoning and Verbal Reasoning, ω_s was small across almost all ages, although it tended to increase at older

ages, especially for the Dutch IDS-2, accompanied by a decrease in ω_h . For Processing Speed and Auditory Short-Term Memory, ω_s was relatively large across all ages. While for Processing Speed, ω_s was larger than ω_h at younger ages and the two become similar at older ages, for Auditory Short-Term Memory the two were similar at younger ages, and ω_s increased at older ages, especially for the Dutch IDS-2. For Visual-Spatial Short-Term Memory, ω_s was relatively large at younger ages and then dropped to typical at older ages, with ω_h going in the opposite directions for the Dutch IDS-2. For the German IDS-2, ω_s increased first from typical to relatively large, and then dropped again to typical at age 20, again with ω_h going in the opposite direction. For Long-Term Memory, ω_s increased from small to relatively large and plateaued at a higher level for the German compared to the Dutch IDS-2 at older ages. Finally, ω_s was always small for Reading and Writing for the Dutch IDS-2, and mostly typical for the German IDS-2.

Discussion

We evaluated the factor structure of the IDS-2 intelligence and basic skills domains using CFA on the Dutch data. Subsequently, we evaluated the measurement invariance of this factor structure across language versions, gender, and age.

RQ 1: Factor Structure

The results showed a higher-order model comparable to the model found in AUTHORS (2020) to be the best representation of the structure of the intelligence and basic skills domains for the Dutch IDS-2. This model includes five theoretical IDS-2 broad ability factors, the two factors Abstract Visual Reasoning and Reading and Writing, and a second-order general intelligence factor. In contrast to many other intelligence tests, where bifactor models clearly outperformed their higher-order counterparts (e.g., Cucina & Byle, 2017), the bifactor version did not fit substantially better than our selected higher-order version. One

explanation for the small difference in fit here might be that additional constraints were necessary for the bifactor models because many factors had only two indicators. This rendered them more similar to the higher-order versions. It is thus important not to overinterpret this finding as support for a higher-order conception of intelligence.

In contrast to AUTHORS (2020), and contrary to our expectation, the theoretical factors Verbal Reasoning and Long-Term Memory were separable in the current study. However, in contrast to the theoretical IDS-2 model, Story Recall showed a cross-loading on Verbal Reasoning, suggesting that, besides long-term memory, this subtest also captures verbal abilities through the memorization and recall of exclusively verbal information. In addition, all three subtests measuring Verbal Reasoning in the final model require crystallized knowledge and are therefore related to Comprehension Knowledge (Gc).

In line with Baddeley's (2003) working memory model and empirical findings (Alloway et al., 2006), but in contrast to the CHC model, our results suggest that Auditory and Visual-Spatial Short-Term Memory can be separated at the broad ability level and not only at the narrow ability level (e.g., Schneider & McGrew, 2018). This finding supports the IDS-2 structure and it might explain why visual memory tasks often do not load on a common factor with verbal memory tasks (Keith & Reynolds, 2010).

Like in AUTHORS (2020), the theoretical IDS-2 factors Visual Processing and Abstract Reasoning collapsed to one factor, Abstract Visual Reasoning, which also included the LMR subtest. This finding is in line with previous results (e.g., Canivez et al., 2017; 2021; Keith & Reynolds, 2010), especially when fluid intelligence is measured using visual materials. Even in cases where both Visual Processing and Fluid Reasoning were measured with both verbal and nonverbal/visual content, the factors were often not separable (e.g., DiStefano & Dombrowski, 2006). Thus, these two presumed abilities are (1) not measured validly in the aforementioned tests, and/or (2) so highly correlated that it is hard to measure

them separately, or (3) in fact one ability. If (1) is true, then more valid tests of both abilities are needed, which requires clear, technical definitions of these abilities (Beaujean & Benson, 2019). If (2) or (3) are true, then it is not useful to create separate scores for Visual Processing and Fluid Reasoning.

In line with the CHC model and with results from AUTHORS (2020), the basic skills domain (i.e., mathematical, reading, and writing skills) was not separable from the intelligence domain. In the theoretical IDS-2 model, the Basic Skills factor correlated to .97 with the general intelligence factor. This high correlation between general intelligence and academic achievement has also been found for other tests (e.g., Kaufman et al., 2012). Our results showed a high loading of the Reading and Writing on the general intelligence factor. LMR showed the highest loading on Abstract Visual Reasoning in the final higher-order model and showed by far the largest *g* loading in the bifactor version. This suggests that it is mainly reasoning abilities, as opposed to knowledge, that create between-subjects variance in LMR (cf. Wasserman, 2019). These findings draw into question the separation of intelligence and basic skills in the IDS-2, and they are in line with various empirical findings that also speak against separating intelligence and academic achievement. For example, intelligence appears to be influenced by the type of school a child attends (Becker et al., 2012) and is thus not independent from learning experiences. Also, PISA test scores, which are in large part measures of academic achievement, appear to reflect mostly general intelligence (Pokropek et al., 2021). Moreover, intelligence tests often contain items that are very similar to those of achievement tests (Naglieri, 2014). Thus, at least in Western societies, intelligence and learning experience are interdependent, which might in turn cause performance in intelligence and academic achievement tests to be highly correlated. In this respect, we agree with Carroll (1993) who argued that achievement variables should not to be viewed as

cognitive abilities of their own, but as the result of cognitive abilities paired with individual learning experiences.

RQ 2: Measurement Invariance Across Language Versions

Full measurement invariance was supported for the final model across the Dutch and German IDS-2 versions. This means that the standardized scores used in practice are comparable between the Dutch and German populations and that the two IDS-2 versions measure the same constructs with comparable reliability for the intelligence and basic skills domains.

RQ 3: Measurement invariance across gender

For both versions, we found full metric invariance, partial scalar invariance, and—based on that—partial strict invariance across gender. Full metric invariance was supported; hence, the same constructs are measured across gender. The fact that only partial scalar invariance was supported is in line with results on other tests (e.g., Irwing, 2012; Schweizer et al., 2018) and on the German IDS-2 (Grob & Hagmann-von Arx, 2018). Females scored higher (0.39 - 0.44 *SD*, respectively) on a subtest measuring visual long-term memory (i.e., Picture Recall) for the Dutch and the German IDS-2, which is in line with previous findings (e.g., Schweizer et al., 2018; see Born et al., 1987, for a meta-analysis), while males scored 0.25 *SD* higher on a subtest on visual-spatial abilities (i.e., Shape Design) for the Dutch IDS-2, also in line with previous findings (see Born et al., 1987; Voyer et al., 1995, for meta-analyses). The fact that females scored 0.41 *SD* higher in Spelling for the German IDS-2 is in line with previous findings on a female advantage in reading and writing skills (see Roivainen, 2011, for a review). Based on the partial invariance of intercepts, the invariance of first-order factor means, residuals, and first-order factor disturbances was also supported. This means that the constructs' reliabilities are comparable across gender. The demonstration of at least partial measurement invariance for both IDS-2 versions implies that it is not

necessary to split the sample into males and females when examining these IDS-2 domains, or to create separate norms for males and females (cf. Steenkamp & Baumgartner, 1998).

RQ 4: Age Invariance

Across an age span of 7 to 20 years, most first-order loadings and residuals, and all second-order loadings, were invariant, with more invariant parameters for the German compared to the Dutch IDS-2. We found most variability across age for Mixed Digit and Letter Span of the Dutch version. With increasing age it becomes a better indicator of Auditory Short-Term Memory, which implies that this subtest has increasing reliability with age.

While the model fitted well for children and younger adolescents, fit was no longer acceptable for older adolescents. Further analyses ruled out that this was due to a change in the relationship between intelligence and basic skills with age. Modification indices did not provide any further insights into possible sources of misfit. However, a subsequent EFA indicated that the nonsalient loadings (i.e., loadings $< .30$) were larger at specific ages compared to for the whole sample. For example, 60% of the absolute nonsalient loadings were larger for 17- to 20-year-olds (sum of loadings = 6.54) compared to for the whole sample (sum of loadings = 4.87) for the German IDS-2. Setting these larger nonzero loadings to zero in the CFA might explain why model fit was worse at specific ages compared to for the whole sample (Schmitt, 2011).

The large bootstrapped confidence intervals for some parameters show that there may be determination problems at some points of the model, probably due to the few indicators per factor (Marsh et al., 1998). This is especially pronounced for the loadings of Story Recall, Picture Recall, and Long-Term Memory, probably due to the cross-loading of Story Recall. These determination problems are ameliorated if the cross-loading of Story Recall on Verbal Reasoning is omitted, but at the cost of worse model fit.

Despite these caveats, our results demonstrate that the identified factor structure was largely invariant across an age span of 7 to 20 years.

Relative Importance of General Intelligence Versus Broad Abilities

McDonald's Omegas revealed a strong general intelligence factor and relatively weak broad ability factors for the IDS-2 intelligence and basic skills domains. This is in line with previous findings from AUTHORS (2020) and with findings on other major intelligence tests (e.g., Canivez et al., 2017; 2021; Cucina & Howardson, 2017). Consequently, the true score variance due to general intelligence seems sufficient for interpretation of a full-scale IQ. Based on the empirically derived thresholds suggested by Gignac and Kretzschmar (2017), the true score variance due to the broad abilities was deemed small for Abstract-Visual Reasoning, small to typical for Verbal Reasoning, typical to relatively large for Visual-Spatial Short-Term Memory and Long-Term Memory, and relatively large for Processing Speed and Auditory Short-Term Memory. For Reading and Writing, there was an apparent difference between the Dutch and the German IDS-2, where this share of true score variance was small for the former and typical to relatively large for the latter. However, with small exceptions, the true score variance due to the broad abilities was always less than .50, casting doubt on the justification of broad ability composites as good indicators of the respective broad abilities.

Implications

The accumulating evidence against the separability of Fluid Reasoning and Visual Processing challenges the CHC model and calls for further research clarifying their status in the structure of intelligence. For the IDS-2, this suggests that the scores for Visual Processing and Abstract Reasoning should best be combined to one score for interpretation. Furthermore, the factor structure of the IDS-2 in general and the relationship between intelligence and

academic achievement more specifically should be studied further with specific samples, such as ones with specific learning disabilities or irregular learning history.

Results from the invariance analyses suggest that scores derived according to the final model identified here will be comparable across language versions, gender, and age, but more indicators per factor would help get better-defined factors at all ages, especially for Verbal Reasoning and Long-Term Memory. Although the final model for the Dutch IDS-2 was slightly different to the model identified in the German IDS-2 (i.e., separate Verbal Reasoning and Long-Term Memory factors with a cross-loading instead of a combined Semantic Long-Term Memory factor), the fact that measurement invariance was found across language versions based on the final model shows that this model also fits the German data well. The metric invariance across gender means that, despite some gender differences in average subtest scores, IDS-2 scores can fairly be compared between girls and boys. This is important, because the test score should indicate the intelligence level as compared to same-aged peers, independent from gender. Therefore, separate norms for girls and boys would not have been desirable. In a similar vein, the found invariance across age means that IDS-2 scores can fairly be compared between different ages, which is especially relevant when testing a child multiple times at different ages. Especially the full invariance of all second-order loadings suggests neither age differentiation nor age dedifferentiation (Tucker-Drob, 2009). According to the ability differentiation hypothesis, however, narrow abilities become more differentiated and thus less correlated with increasing ability levels (e.g., Facon et al., 2011; MacLean et al., 2011). An important follow-up question would be if this differentiation can be found in relation to intelligence level rather than age.

Finally, omegas indicate that carefulness is required when interpreting broad ability composites and intelligence profiles. This finding has now been replicated for many intelligence tests. On the one hand, this challenges the usefulness of the CHC model, with its

emphasis on broad abilities, for the development of individually administered intelligence tests (cf. Beaujean & Benson, 2019). From a statistical point of view, it also yields the question if factors lacking incremental validity should be left out of the model. On the other hand, the general factor could also be seen as a statistical finding that is simply the sum of all influences which cause all cognitive abilities to be positively correlated (Schneider & McGrew, 2018). From a practice point of view, even though the overall score on an intelligence test appears the most reliable, we cannot ignore the fact that an impression of the child's cognitive strengths and weaknesses is essential for tailoring support to the needs of an individual child. It needs to be determined under what circumstances broad ability composites and profile analyses can be used without risking mis- or overinterpretations. One way to test this in future research will be by using the combined data of the IDS-2 standardization samples across Europe.

Limitations

A major limitation of this study is the small number of indicators per factor for most of the tested models. This might have contributed to some of the local fit problems (cf. Marsh et al., 1998). Given the weak broad abilities and potential issues in structural validation, adding more subtests per broad ability should be considered for future adaptations of the IDS-2, taking into account practical time constraints and the danger of fatigue effects. This could help better distinguish Long-Term Memory and Verbal Reasoning, for example.

The criteria used to determine invariance were much stricter for LSEM than for the MGCFA, which has possibly contributed to finding more noninvariance across age than across language versions. Lately, a method of invariance testing has been developed for LSEM that is more similar to MGCFA, namely joint estimation (Hartung et al., 2021; Robitzsch, 2020). Using this method might have resulted in even more noninvariant parameters across age.

Another limitation is the relatively small Austrian sample ($n = 76$), combined with the sample not being entirely representative, especially with respect to native language. Although we do not aim to draw specific conclusions about the Austrian population, this does limit the generalizability of our findings to the whole German-speaking population.

Conclusion

The theoretically proposed structure for the intelligence and basic skills domains of the Dutch and the German IDS-2 was mostly supported, but some factors collapsed and the two domains were not separable. The final model selected here was an empirically determined model suggested by prior EFA of the German IDS-2. This final model was fully invariant across the Dutch and the German IDS-2 and largely invariant across gender and age, suggesting that IDS-2 scores corresponding to the factors in the final model are comparable across these populations. Finally, the IDS-2 subtests were indicators of a strong general intelligence factor and relatively weak broad ability factors, suggesting that interpretation of broad ability composites should be made with caution.

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All analysis scripts are available at

https://osf.io/azep6/?view_only=2245011a37aa48aab00709c646a31d03. We report how we determined our sample size, all data exclusions (if any), all data inclusion / exclusion criteria, whether inclusion/exclusion criteria were established prior to data analysis, all measures in the study, and all analyses including all tested models. If we use inferential tests, we report exact p values, effect sizes, and 95% confidence or credible interval

IDS-2 MEASUREMENT INVARIANCE

Table 1

Fit Indices and Model Comparisons for the Intelligence and Basic Skills Domains for the Dutch IDS-2

	Model/Comparison	$(\Delta)\chi^2$	$(\Delta)df$	$(\Delta)CFI$	$(\Delta)RMSEA$ [90% CI]	$(\Delta)SRMR$	$(\Delta)AIC$
	0. <i>g</i>	1,728.78***	119	.791	.098 [.093, .102]	.059	112,719.99
Higher-order	1. EFA-based SLM	551.63***	113	.943	.052 [.048, .057]	.038	111,554.84
	2. EFA-based VR_LM	445.63***	111	.957	.046 [.042, .051]	.034	111,452.84
	3. IDS-2	496.21***	111	.950	.049 [.045, .054]	.036	111,503.42
	4. CHC w/o Gq	485.26***	110	.951	.049 [.045, .053]	.036	111,494.47
	5. CHC w/ Gq	469.12***	110	.953	.048 [.043, .052]	.035	111,478.33
Bifactor	6. EFA-based SLM	479.99***	106	.952	.050 [.045, .054]	.037	111,497.20
	7. EFA-based VR_LM	401.60***	106	.962	.044 [.040, .049]	.033	111,418.81
	8. IDS-2	496.21***	111	.950	.049 [.045, .054]	.036	111,503.42
	9. CHC w/o Gq	466.88***	108	.953	.048 [.044, .053]	.035	111,480.09
	10. CHC w/ Gq	469.42***	110	.953	.048 [.044, .052]	.035	111,478.63
Bifactor(S-1)	11. EFA-based SLM	569.49***	111	.941	.054 [.050, .058]	.038	111,576.70
	12. EFA-based VR_LM	482.63***	111	.952	.049 [.044, .054]	.036	111,489.84
	13. IDS-2	520.12***	112	.947	.051 [.046, .055]	.037	111,525.34
	14. CHC w/o Gq	492.88***	111	.950	.049 [.045, .054]	.036	111,500.09
	15. CHC w/ Gq	492.88***	111	.950	.049 [.045, .054]	.036	111,500.09
	2. versus 7.	44.03***	5	-.0051	.0018	.0011	34.03
	1. versus 2.	106.00 ^a	2	-.0135	.0062	.0033	102.00

Note. $N = 1,423$. Fit indices and degrees of freedom are displayed for Models 0 to 15, and delta fit indices and change in degrees of freedom for model comparisons (last two rows).

Dark grey: Local fit not acceptable (see Table S5). Light grey: global fit not acceptable. Bold: final adopted model.

The thresholds for good global fit are $SRMR \leq .08$, together with $CFI \geq .95$ or $RMSEA \leq .06$.

The cutoffs for the delta fit criteria are $\Delta CFI < -.01$, $\Delta RMSEA < .015$, and $\Delta SRMR < .03$.

EFA = exploratory factor analysis; IDS-2 = Intelligence and Development Scales-2; CHC = Cattell–Horn–Carroll; *g* = general intelligence; CFI = comparative fit index; RMSEA = root mean square error of approximation; CI = confidence interval; SRMR = standardized root mean square residual; AIC = Akaike information criterion.

^a nonnested models, no χ^2 -difference test performed; *** $p < .001$.

IDS-2 MEASUREMENT INVARIANCE

Table 2

Results From Invariance Analyses Across the Dutch and German IDS-2 Versions for the Final Model for the Intelligence and Basic Skills Domains

Model	χ^2	df	CFI	RMSEA [90% CI]	SRMR	Comp.	$\Delta\chi^2$	Δdf	ΔCFI	$\Delta RMSEA$	$\Delta SRMR$
A. Configural	913.16***	222	.957	.047 [.044, .050]	.035						
B1. First-order loadings	940.97***	232	.956	.046 [.043, .050]	.038	vs. A	27.81***	10	-.0011	-.0004	.0024
B2. Second-order loadings	960.07***	239	.955	.046 [.043, .049]	.041	vs. B1	19.09***	7	-.0008	-.0003	.0029
C1. Intercepts	989.80***	249	.954	.046 [.044, .049]	.041	vs. B2	29.73***	10	-.0012	-.0003	.0004
C2. First-order factor means	1,023.55***	256	.952	.046 [.043, .049]	.042	vs. C1	33.75***	7	-.0017	.0002	.0007
D1. Residuals	1,097.85***	273	.948	.047 [.044, .049]	.043	vs. C2	74.30***	17	-.0036	.0002	.0009
D2. First-order factor disturbances	1,106.01***	281	.948	.046 [.043, .048]	.043	vs. D1	8.17***	8	-.0000	-.0007	.0004

Note. $N = 2,828$. Results from multiple-group confirmatory factor analyses testing

increasingly constrained models are displayed. The models are as follows: (A) Configural invariance; (B1) and (B2) metric invariance of first-order and second-order loadings; (C1) and (C2) scalar invariance at the manifest and first-order factor level; (D1) and (D2) strict invariance at the manifest and first-order factor level. The thresholds for good global fit are $SRMR \leq .08$, together with $CFI \geq .95$ or $RMSEA \leq .06$. The cutoffs for the delta fit criteria are $\Delta CFI < .01$, $\Delta RMSEA < .015$, and $\Delta SRMR < .01$ for invariance of intercepts and residuals, or $\Delta SRMR < .03$ for all other forms of invariance. CFI = comparative fit index; RMSEA = root mean square error of approximation; CI = confidence interval; SRMR = standardized root mean square residual; Comp. = model comparison; IDS-2 = Intelligence and Development Scales–2.

** $p < .01$. *** $p < .001$.

IDS-2 MEASUREMENT INVARIANCE

Figure 1

Higher-Order Models for the Intelligence and Basic Skills Domains

Stratum / Subtest	g	EFA-based SLM	EFA-based VR_LM	IDS-2	CHC w/o Gq	CHC w/ Gq
IV						
III		g	g	g	g	g
II	g	AVR PS ASM VSM SLM RW	AVR PS ASM VSM VR LM RW	VP PS ASM VSM AR VR LM BS	Gv Gs $\frac{Gwm}{Wa Wv}$ Gf Gc Glr Grw	Gv Gs $\frac{Gwm}{Wa Wv}$ Gf Gc Glr Gq Grw
SDE	•	•	•	•	•	•
WD	•	•	•	•	•	•
PA	•	•	•	•	•	•
BO	•	•	•	•	•	•
DLS	•	•	•	•	•	•
MDLS	•	•	•	•	•	•
SM	•	•	•	•	•	•
RSM	•	•	•	•	•	•
MC	•	•	•	•	•	•
MO	•	•	•	•	•	•
NC	•	•	•	•	•	•
NO	•	•	•	•	•	•
SR	•	•	•	•	•	•
PR	•	•	•	•	•	•
LMR	•	•	•	•	•	•
RE	•	•	•	•	•	•
SPE	•	•	•	•	•	•

Note. The double-headed arrow indicates a latent correlation. g = general intelligence; EFA = exploratory factor analysis; IDS-2 = Intelligence and Development Scales–2; CHC = Cattell–Horn–Carroll; Gv = Visual Processing; Gs = Cognitive Processing Speed; Gwm = Working Memory Capacity; Gf = Fluid Reasoning; Gc = Comprehension–Knowledge; Glr = Long-Term Storage and Retrieval; Grw = Reading and Writing; Gq = Quantitative Knowledge; AVR = Abstract Visual Reasoning; PS = Processing Speed; ASM = Auditory Short-Term Memory; VSM = Visual–Spatial Short-Term Memory; (S)LM = (Semantic) Long-Term Memory; RW = Reading and Writing; VR = Verbal Reasoning; VP = Visual Processing; AR = Abstract Reasoning; BS = Basic Skills; Wa = Auditory Short-Term Storage; Wv = Visual–Spatial Short-Term Storage; SDE = Shape Design; WD = Washer Design; PA = Parrots; BO = Boxes; DLS = Digit and Letter Span; MDLS = Mixed Digit and Letter Span; SM = Shape Memory; RSM = Rotated Shape Memory; MC = Matrices: Completion; MO = Matrices: Odd One Out; NC = Naming Categories; NO = Naming Opposites; SR = Story Recall; PR = Picture Recall; LMR = Logical–Mathematical Reasoning; RE = Reading; SPE = Spelling.

Figure 2

Standardized Parameter Estimates, Model Fit, and McDonald's Omegas for the Final Model (Model EFA 2) for the Intelligence and Basic Skills Domains of the Dutch (Panel A) and German (Panel B) Intelligence and Development Scales–2

Note. $N_{\text{Dutch}} = 1,423$; $N_{\text{German}} = 1,405$. All parameters were significant with $p < .001$. g = general intelligence; AVR = Abstract Visual Reasoning; PS = Processing Speed; ASM = Auditory Short-Term Memory; VSM = Visual–Spatial Short-Term Memory; VR = Verbal Reasoning; LM = Long-Term Memory; RW = Reading and Writing; SDE = Shape Design; WD = Washer Design; MC = Matrices: Completion; MO = Matrices: Odd One Out; LMR = Logical–Mathematical Reasoning; PA = Parrots; BO = Boxes; DLS = Digit and Letter Span; MDLS = Mixed Digit and Letter Span; SM = Shape Memory; RSM = Rotated Shape Memory; NC = Naming Categories; NO = Naming Opposites; SR = Story Recall; PR = Picture Recall; RE = Reading; SPE = Spelling; CFI = comparative fit index; RMSEA = root mean square error of approximation; CI = confidence interval; SRMR = standardized root mean square residual; AIC = Akaike information criterion; ω_t = omega total; ω_h = omega hierarchical; ω_s = omega subscale.

Figure 3

Fit Measures for the Final Model for the Dutch and German Intelligence and Development Scales–2 (Model EFA VR_LM) for the Intelligence and Basic Skills Domains Across Age, Determined With Local Structural Equation Modeling

Note. Gray and black dots indicate significantly lower and not significantly different values, respectively, compared to the average from the permuted data sets. The gray-shaded areas indicate values beyond the thresholds of the displayed fit indices: $CFI \geq .95$, $RMSEA \leq .06$, and $SRMR \leq .08$. CFI = comparative fit index. RMSEA = root mean square error of approximation; CI = confidence interval; SRMR = standardized root mean square residual.