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training

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Highlights

- The link between computer-based training and high-stakes assessments was

  investigated.

- Training and selection test data of 15,752 pilot trainee applicants was analyzed.

- The amount of training predicted test performance in curvilinear fashion as expected.

- The ability test scores' structure was invariant across different amounts of training.

- Free training was not linked to the psychometric structure of the high-stakes tests.

Measurement and structural invariance of cognitive ability tests after computer-based training

Abstract

Ability tests are core elements in performance research as well as in applied contexts and are increasingly carried out using computer-based versions. In the last few decades a whole training and coaching industry has developed to prepare individuals for computer-based assessments. Evidence suggests that such commercial training programs can result in score gains in ability tests, thereby creating an advantage for those who can afford it and challenging the fairness of ability assessment. As a consequence, several authors recommended freely offering training software to all participants to increase measurement fairness. However, it is still an open question whether the unsupervised use of training software could have an impact on the measurement properties of ability tests. The goal of the present study is to fill this gap by examining the subjects' ability scores for measurement and structural invariance across different amounts of computer-based training. Structural equation modeling was employed in a sample of 15,752 applicants who participated in high-stakes assessments with computer-based ability tests. Across different training amounts, our analyses supported measurement and structural invariance of ability scores. In conclusion, free training software is a means that provides fair preparation opportunities without changing the measurement properties of the tests.

Keywords: computer-based training, computer-based testing, cognitive ability, measurement invariance, test fairness

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training

1. Introduction

In the last decades the use of computers in psychological assessment has grown

enormously. In the domain of cognitive abilities, computer-based assessments have

increasingly substituted paper-pencil tests and are now core elements in performance research

and applied contexts such as personnel selection, admission decisions in educational contexts,

or neuropsychological assessments. In these applications computer-based tests allow the

assessment of cognitive abilities with high levels of standardization and offer the possibility

to realize designs that could not be appropriately implemented with paper-pencil tests (Greiff,

Scherer, & Kirschner, 2017; Tippins, 2015).

However, particularly in high-stakes settings, there are still challenges with cognitive

ability tests. One is the requirement of test fairness in the sense of ensuring that all test takers

have comparable opportunities to demonstrate the abilities measured by the test. With

cognitive ability tests, it is of particular importance to provide examinees with equal

opportunities to prepare for the test (American Educational Research Association, American

Psychological Association, & National Council on Measurement in Education, 1999). In the

interest of fairness, the materials provided should closely resemble the actual test with

regards to appearance and format (American Educational Research Association, American

Psychological Association, & National Council on Measurement in Education, 2014). Yet,

the requirement of equal opportunities for test preparation is increasingly challenged by a

growing market of service companies offering commercially distributed training software.

Although the quality of such software may vary substantially between providers, there is

evidence that training[1] may result in substantial score gains in cognitive ability tests, not only

in educational but also in selection settings (Chung-Herrera, Ehrhart, Ehrhart, Solamon, &

Kilian, 2008; Hausknecht, Halpert, Di Paolo, & Moriarty Gerrard, 2007). It can be expected

that only individuals with sufficient financial resources will be able to afford such training

programs, calling into question the fairness of ability assessments (Sackett, Burris, & Ryan,

1989; Stemig, Sackett, & Lievens, 2015). Such training gains can be partly attributed to retest

effects, i.e. score gains resulting from the mere repetition of a test (Freund & Holling, 2011;

Hausknecht et al., 2007). This implies that not only individuals with training course

experience but also individuals who had the opportunity to repeat an examination may have

an advantage over individuals who conduct an ability test for the first time. Taken together,

commercially available training and the retest policies of institutions give rise to considerable

concern about the fairness of these ability assessments. To deal with this problem, several

authors suggested to freely offer training and practice materials to all participants (Arendasy

et al., 2016; Freund & Holling, 2011; Sackett, Borneman, & Connelly, 2008; Zwick, 2002).

For example, Arendasy et al. (2016) proposed that "making more informal student-centered

practice opportunities accessible to all test-takers could resolve issues of fairness associated

with differential access to test preparation opportunities without compromising measurement

fairness" (p. 54).

    Today most organizations involved in high-stakes computer-based testing actually

provide opportunities for test familiarization by distributing free practice items or tutorials as

recommended by the International Test Commission (The International Test Commission,

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[1] It is important to note that the terms training, practice, retest, and coaching are not
exclusive categories but belong a continuum of preparation activities, with different
emphasis on test familiarization and the development of test-specific skills (Arendasy,
Sommer, Gutiérrez-Lobos, & Punter, 2016; Messick & Jungeblut, 1981).

2006). The range of complexity of practice materials currently offered by test-administering

institutions is, however, mostly restricted to downloadable information brochures and

example items in paper and pencil format. There is some slightly more sophisticated online

material available. It must be expected though, that in case of cognitive ability tests, the

practice gains increase as a function of the equivalence of the practice items with test items

(Hausknecht et al., 2007). Therefore, to ensure test fairness, it is crucial to offer practice

items that resemble the test items as closely as possible. Recently, more efforts have been

made to increase fairness. In the United States for example, the College Board cooperated

with the Khan Academy to offer freely available test practice programs for the SAT (formerly

Scholastic Aptitude Test), a common test for college admissions. Overall, however, still only

little consideration is given to the unequal opportunities to practice and training activities, for

example by making effective preparation material freely available to all test takers and

informing them openly about available training options.

One reason for this deficiency may be that in the context of personnel selection there

is virtually no published research on the effects and consequences of using sophisticated

computer-based training tools, especially on the validity of the tests. This is surprising given

the great potential of computer-based training tools in this field. With computer-based

systems it is possible to offer training tools with high equivalence to selection tests. Such

systems allow a very standardized presentation of training items (including timing and

navigation issues), complex interfaces and item-selection algorithms, a wide range of

multimedia features, reliable response recording, or feedback mechanisms. Finally,

computer-based training systems can be economically distributed, making them especially

attractive for larger user pools.

2. Possible effects of training

For the current study possible consequences of practice and training are inferred from two related research areas. The first area comprises research regarding practice and retest effects (Sackett et al., 1989; Scharfen, Peters, & Holling, 2018; Van Iddekinge & Arnold, 2017), the second includes research regarding the acquisition of cognitive skills (Ackerman, 1987, 1988; Fitts, 1964).

Since Ebbinghaus' learning experiments it is well-established that practice of cognitive tasks normally results in asymptotic learning curves (Donner & Hardy, 2015; Heathcote, Brown, & Mewhort, 2000; Newell & Rosenbloom, 1981). Practice effects seem to occur in virtually all types of mental ability tests, with especially large sizes of effect for psychomotor coordination and spatial orientation tests (Sackett et al., 1989). Practice effects are generally larger when identical compared to alternate test forms are employed, i.e. practice gains increase the more equivalent both test forms are (Hausknecht et al., 2007; Scharfen et al., 2018). Since training with computer-based training modules can be considered as practice with parallel test forms, the possible consequences of freely offering training software on measurement properties may be derived from studies that analyze the impact of practice and retesting on test validity.

Although research has shown that criterion-oriented validity is either unaffected or positively affected by practice and retest effects (Van Iddekinge & Arnold, 2017), the empirical literature for construct validity is rather mixed. An early study with psychomotor tests showed that the factor structure of a psychomotor task changed over practice to a simpler pattern (Fleishman & Hempel, 1954). Current research has demonstrated evidence of measurement invariance over retest scores of several cognitive ability tests (Reeve & Lam, 2005) but also of non-invariance (Lievens, Reeve, & Heggestad, 2007). Here, variance in retest scores reflected test-specific abilities to a larger degree than variance of initial scores. This could be attributed to a reduction of construct irrelevant variance, like reduced test

anxiety or greater experience with the test and the test setting (Hausknecht et al., 2007;

Lievens, Buyse, & Sackett, 2005; Van Iddekinge & Arnold, 2017). However, to our

knowledge, there is no research on the question whether different training quantities could

have an impact on the invariance of cognitive ability measurements. Different amounts of

training could influence the measured variables without changing the basic ability of interest,

thereby creating measurement bias. Likewise, different amounts of training could change the

relations between different constructs.

For the invariance of cognitive ability measurement theories of skill acquisition play

an important role as well. Most of these theories suggest that practice of cognitive or

psychomotor tasks may lead to the development of a (rather narrow) skill set (Fitts, 1964;

Rosenbaum, Carlson, & Gilmore, 2001). Therefore, there is a certain risk that the intense use

of computer-based training tools for cognitive tasks results in a change of the construct from

a rather broad ability to a narrow skill. In this case, the test conducted after extensive practice

would not be useable to measure the ability. Ackerman (1987, 1988) presented a

comprehensive theory which states that by practice, a skill is acquired in three phases in

which different determinants are important for individual performance: content abilities in the

first phase (which correspond to different aspects of intelligence), perceptual speed in the

second, and psychomotor skills in the third phase. For the construct-oriented validity of a

cognitive test this implies that for those who have the opportunity to practice, in every phase

of skill acquisition (depending on the amount of practice) the test would assess a different

underlying ability. Importantly, Ackerman's theory states that skill acquisition is only

pertinent if the practice material is rather consistent and not complex (see also Ackerman &

Schneider, 1985). For the construction of cognitive ability tests this implies that the test

material should be rather complex and have an inconsistent structure so that even after

intense practice, test-takers should never reach phases two or three of skill acquisition.

3.   Goals of the current study

Ability diagnostic in high-stakes settings is in the predicament that on the one hand providing free training opportunities is a promising way to (re-) establish fair initial conditions for every test-taker. On the other hand, this opportunity to practice increases the risk that test-takers may develop a cognitive skill in the tasks in question, thereby compromising the construct validity of the cognitive tests. For the context of personnel selection Ackerman's theory (1987, 1988) shows a way of how the development of skills as a consequence of training may be prevented and the construct validity may be preserved: The nature of the tasks in the cognitive ability tests has to be more complex and inconsistent, so that more sophisticated and changing mental operations are required for the test items. The ability tests used in the present study were developed with a special focus on more complex and inconsistent material and items. Therefore we expected that training did not alter the measurement structure and the relations between constructs.

Hypothesis 1: Increasing levels of training do not alter the factor structure of the measurements.

Likewise, with reference to Ackerman's framework there should be a consistent relationship between the ability constructs and perceptual speed as well as psychomotor coordination for different practice levels.

Hypothesis 2a: Increasing levels of training do not alter the importance of perceptual speed within the factor structure.

Hypothesis 2b: Increasing levels of training do not alter the importance of psychomotor coordination within the factor structure.

In both cases we expect that the size of the respective factor loadings is not moderated by the amount of training. The goal of this study was to test these hypotheses in a sample of $N = 15,752$ applicants whose data were gathered in high-stakes application contexts. Since

the applicants were encouraged to use our freely distributed computer-based training tools,

this sample provided a unique opportunity to test these hypotheses in a sample with high

external validity. In contrast to previous studies, we used computer-based training tools that

were specifically designed to resemble the different cognitive ability tests as closely as

possible. In addition, the applicants provided data on their amount of individual training so

that a quantitative measure of these training activities was available.

4. Method

4.1. Participants and procedure

The present sample consisted of candidates applying for a pilot trainee position at

major European airlines. Applicants were included in the present study if they had

participated in an assessment between 2010 and 2017. During this period, all applicants were

offered identical computer-based training programs and conducted the same ability tests. The

present study only considered applicants who had participated for the first time in an

assessment in our institution. Data sets with missing values were excluded from the analyses

(there were 100 applicants, i.e. 0.63 % of the sample with incomplete training data) so that

only complete data sets were used. The remaining 15,752 candidates were between 17 and 50

years old ($M = 20.30$, $SD = 2.68$), 86% were male and 14% were female. All applicants had

completed a high school education adequate for university entrance.

In the following data from a multi-stage selection procedure were analyzed. The

procedure started with a set of computer-based tests measuring cognitive abilities, knowledge

and psychomotor abilities, as required for aviation training and the pilot's profession. Further

stages comprised a flight in a fixed-base flight simulator, an assessment center, and an

interview. Examinations with computer-based tests were conducted in groups of up to 44

subjects. The measurement procedure was highly standardized; all tests were administered at

the same time of the day and in an identical order. Applicants completed all tests within one

day, in an air-conditioned and well-lit testing room. Each ability test started with an

introductory text on the screen; the cognitive ability tests also included examples and a few

practice items. Before the main test began, comprehension questions were answered by the

test administrator if necessary.

4.2. Measures

For the present study, we analyzed nine computer-based tests. Six tests measured

basic cognitive abilities: visual perception speed, selective attention, auditory and visual

memory capacity, mental rotation and spatial visualization (both aspects of spatial abilities).

In order to examine possible effects of the training on the relation between the measured

construct of cognitive ability and other constructs, we also included two tests measuring

technical knowledge and comprehension and one test measuring psychomotor coordination

and the capacity for multiple task coordination. All tests have been developed in our

institution and are employed in pilot selection for several years. The following cognitive

ability tests were employed:

The Optical Perception Test (test-retest reliability r_{tt} = .90; Zierke, 2014) as a measure

of visual perception speed required the subject to read four specific indicator values from a

complex display consisting of nine dials. The dials differed in color (black/white) and shape

(round/angular) and were displayed for two seconds. Before each task was presented,

information was given about which dials were critical (black/white/round/angular) and thus

which had to be read.

The Symbol Concentration Test (r_{tt} = .93; Zierke, 2014) as measure of selective

attention required the subject to apply changing rules to long sequences of displayed

triangles. The triangles differed in color, orientation, and number of dots displayed in each

triangle. Before each sequence, a rule indicated which of these features were critical. The

subjects had to decide whether or not two consecutive triangles were identical with respect to the critical features.

The Running Memory Span Test (r_{tt} = .76; Zierke, 2014) is a measure of auditory memory. It required the subject to memorize acoustically presented sequences of digits and enter them in reverse order. The sequences differed in length of up to 35 digits.

The Visual Memory Capacity Test (r_{tt} = .74; Hermes & Stelling, 2016) contained an n-back task, requiring the subjects to compare a sequence of symbols and to react when the present symbol matched the one from n steps earlier in the sequence. The symbols differed in shape and color. Two-back, 3-back, 4-back, and 5-back sequences were administered.

In the Mental Rotation Test (r_{tt} = .91; Zierke, 2014) the subject had to visualize a cube with one face marked by a cross. Then sequences of acoustic orders were presented— differing in length and speed—which specified how to mentally rotate the cube. At the end of each sequence the subjects had to indicate the position of the mark on the cube.

The material in the Spatial Visualization Test (Cronbach's α = .91; Zierke, 2014) consisted of dice with different dot markings. The subjects saw one unfolded die of which all faces could be seen and five different dice of which three faces could be seen. The task was then to decide which of the five dice was unfolded.

The Test of Knowledge in Physics (Cronbach's α = .78; Zierke, 2014) evaluated the subjects' physics and technical knowledge, which mainly covered scholastic knowledge. The areas included technical systems, mechanics, electronics, thermodynamics, hydraulics, and aerodynamics.

The Mechanical Comprehension Test (Cronbach's α = .78; Zierke, 2014) contained questions covering technical problems which, in most cases, were illustrated by pictures. The test did not assess textbook knowledge but rather measured the understanding of mechanical and physical principles and devices.

The "Monitoring and Instrument Coordination" test provided two measures, one for psychomotor coordination and one for multiple task coordination (r_{tt} = .75 and .76 respectively; Hoermann, 2016). The test was a complex, flight simulator like task mainly operated with a joystick. Different parameters (heading, speed, altitude) had to be coordinated via tracking tasks and button presses. In addition, an auditory secondary task had to be accomplished. The two measures were obtained from different parts of the test: the first represented psychomotor measures of the tracking performance and the second represented the coordination of a complex task consisting of several tracking tasks and the auditory task.

4.3. Training and test preparation

At least three weeks ahead of the computer-based assessment, all applicants were offered online access to the test preparation materials. Here, the computer-based training modules —which are executable software files—could be downloaded for offline use. The download package also included two documents: one contained training recommendations and the other was a template which was be used to record how often each training module was used. With these software modules and documents each candidate had the opportunity and was advised to practice for the ability tests prior to the examination. The training records were submitted on the testing day.

The preparation concept differed between test domains. For basic cognitive abilities like visual perception speed, selective attention, auditory and visual memory capacity, mental rotation, and spatial visualization, the design of each training module resembled the actual test as closely as possible, yet without disclosing any test items. After instructions concerning the test principles, the user chose between up to three levels of difficulty, whereby the highest level equaled the item difficulty in the actual test. To ensure variation of training contents between repeated executions, training items were either randomly drawn at runtime from a larger pool of items or dynamically generated, thereby following specific rules to control item

difficulty. In the training program for the Running Memory Span Test for instance, the series

of numbers that make up an item are randomly generated according to predefined sequence

length specifications and restrictions on the frequency of occurrence and sequence of

individual digits (e.g., to prevent the direct succession of identical digits). At the end of each

training run the candidates received a summarized feedback about the percentage of correctly

solved items. Recommendations were to start the training on the lowest level of difficulty,

then work through all other levels. The same module should not be repeated more than three

times in a row and regular breaks should be introduced. To keep the training varied, training

modules for different abilities should be used alternately. In total each of them should be

worked on 20 times. If candidates had the impression that their performance was still

increasing, they were advised that they should practice even more.

In contrast, the software module for tests of technical knowledge and comprehension

was not developed as a training tool. It merely offered example items for familiarization with

the test principle and the use as a self-diagnostic tool to identify personal deficiencies in the

subject matter. A repetition of the module was recommended only to check the individual

learning progress. Hence, the number of executions of the module could not be interpreted as

an indicator of training quantity. Finally, as the measurement of psychomotor coordination

and the capacity for multiple task coordination requires specific input devices, a different

preparation strategy was chosen. Instead of a software module, the candidates received a

comprehensive information brochure and the actual training took place on the testing day

during a standardized, yet unscored familiarization phase directly before the test.

4.4. Statistical analyses

Test reporting and interpretation for the selection procedure is done on a 9-point

standard scale (stanine). Applicants' raw scores of each ability test are converted to stanine

values based on an archival data set of pilot trainee applicants. These individual stanine

scores were used in the statistical analyses.

In a first step, we analyzed the relationship between the scores of the ability

measurements and the reported number of training runs. In a second step, we assessed

whether increasing numbers of training runs had an impact on the psychometric properties of

ability tests and the relationship between constructs. Our hypotheses 1, 2a, and 2b implied

that with an increasing number of training runs, the relationship between the measured scores

and the underlying (latent) constructs as well as the relationship between constructs remain

unchanged. Such hypotheses can be tested by examining the measurement and structural

invariance of ability scores across different levels of training (Putnick & Bornstein, 2016;

Schmitt & Kuljanin, 2008; Vandenberg & Lance, 2000). As a first step the sample was

divided in six groups, based on the mean number of training runs across the six cognitive

abilities: visual perception speed, selective attention, auditory and visual memory capacity,

mental rotation and spatial visualization (see Table 1). Two of these groups were defined

based on conceptual reasons: the first group contained applicants who had not used any of the

training modules. The last group contained applicants who had used the training modules on

average more often than recommended, i.e. more than 20 runs. The other four groups

included applicants who were situated between these two ends of the training distribution

(with equal ranges in training quantity across groups and reasonable group sizes).

Table 1

Mean number of training runs and sample sizes of training groups

Group No.	Training quantity (X)	N
1	X = 0	60
2	$0 < X \leq 5$	2061
3	$5 < X \leq 10$	3140
4	$10 < X \leq 15$	3578
5	$15 < X \leq 20$	4393
6	X > 20	2520

These six groups were simultaneously analyzed in a multigroup structural equation

model (Putnick & Bornstein, 2016). Cognitive ability, technical comprehension, and complex

psychomotor coordination were conceptualized as latent variables and the test scores (stanine

scores) of the computer-based tests were conceptualized as manifest variables (see Figure 1).
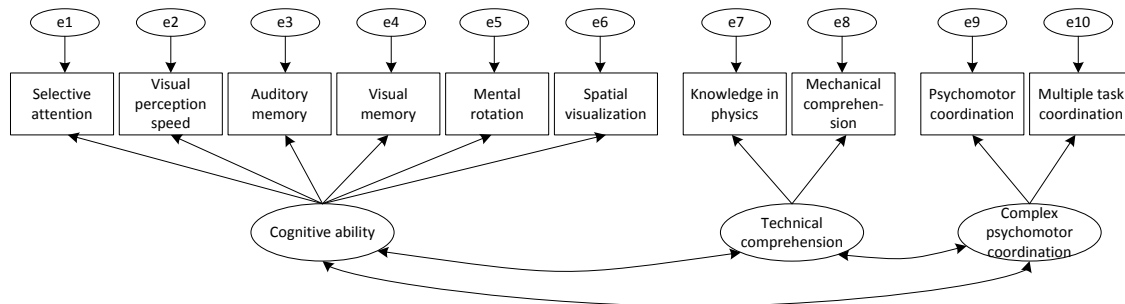

Figure 1. Confirmatory factor analysis model.
[2-column fitting image]

The assessment of measurement and structural invariance involved a sequence of

model comparisons with increasingly stringent models (Putnick & Bornstein, 2016; see Table

2). The first model is the configural invariance model. This is the least stringent model since

it imposes no parameter constraints across groups. With such a model the hypothesis is tested

whether the same tests load on the same latent variables across groups. Within each group,

the factor loading of one manifest variable was set to 1 to achieve model identification. The

second model was the metric invariance model. Here, each factor loading was constrained to

be equal across groups. This model allowed to test whether the amount of computer-based

training has an effect on the relative weights of the constructs on the measured test scores.

The third model was the scalar invariance model. In this model the loadings and the

intercepts of the measured variables were constrained to be equal across groups, which means

that an individual with average ability would have the same expected manifest score on a test,

irrespective of how much they trained. The fourth model was the residual invariance model.

Here, the loadings, intercepts, and residual variances were constrained to be equal across

groups, which states that the amount of variance in manifest indicators not explained by the

latent variables remains the same, irrespective of how much an individual has trained. The

fifth model tests for invariant factor variances; here the variances of the latent factors are

additionally constrained to be equal across groups implying that irrespective of the amount of

training the variability of the latent ability remains the same. The sixth model was the

structural invariance model. In this model, the loadings, intercepts, residual variances, factor

variances, and the covariances between factors were constrained to be equal across groups. If

the structural invariance model can be accepted, it implies that in addition the relations

between latent constructs remain constant across training groups. In this case, the whole

factorial structure of the measurements is not affected by training (hypothesis 1).

Table 2

Overview of equality constraints imposed across training groups

No.	Model	Factor loadings	Intercepts	Residual variances	Factor variances	Factor covariances
1	Configural invariance	free	free	free	free	free
2	Metric invariance	<u>invariant</u>	free	free	free	free
3	Scalar invariance	invariant	<u>invariant</u>	free	free	free
4	Residual invariance	invariant	invariant	<u>invariant</u>	free	free
5	Invariant factor variances	invariant	invariant	invariant	<u>invariant</u>	free
6	Structural invariance	invariant	invariant	invariant	invariant	<u>invariant</u>

Note. All models are nested; the parameter constraint that is tested in a model is underlined.

With reference to the Ackerman model, it was hypothesized that across different

training levels, there should be a constant relationship between the ability constructs and

perceptual speed (hypothesis 2a) and between the ability constructs and psychomotor

coordination (hypothesis 2b). The measurement invariance analyses already serve as omnibus

tests for both hypotheses. In particular, if metric invariance is supported, there is evidence of

a common pattern of loadings across groups. This also comprises the loading of perceptual

speed on the latent cognitive ability factor, i.e. irrespective of the amount of training, the

relationship between the latent variable and its indicators is not changed. To more specifically

test hypothesis 2a, we compared the metric invariance model to a modified model where only

the loading of perceptual speed on the latent cognitive ability factor was released. If there is

no significant difference between both models, this indicates that the importance of

perceptual speed was not changed due to different amounts of training: the size of the loading

remained the same independent of training (Byrne, 2016). A similar analysis can be

performed for psychomotor coordination (hypothesis 2b). Again, the metric invariance model

can be compared to a modified model, in this case, psychomotor coordination was allowed to

load on the latent cognitive ability factor. If there is no significant difference between the

metric invariance and this modified model, it more specifically indicates that the importance

of psychomotor coordination was not changed as a result of different amounts of training.

The nested structural equation models were analyzed using the statistics environment

R (version 3.4.3; R Core Team, 2017) together with the "lavaan" package (version 0.5-23;

Rosseel, 2012). Maximum likelihood was employed to estimate the model parameters. Model

fit of the *baseline/configural model* was assessed by a set of approximate fit indices:

comparative fit index (CFI), root mean square error of approximation (RMSEA), and

standardized root mean square residual (SRMR). The configural model was considered

acceptable with CFI ≥ .95, RMSEA < .08, and SRMR < .08 (Byrne & Stewart, 2006). Chi-

square was not used as an acceptance criterion since chi-square is overly sensitive to sample

size (Bentler & Bonett, 1980; Cheung & Rensvold, 2002) and chi-square is not considered as

an appropriate criterion in very large samples (Rutkowski & Svetina, 2013).

When chi-square is used as a criterion in large samples such as the present study,

models tend to be rejected even due to differences of trivial size. However, it is not enough to

claim that the chi-square value is inflated by sample size (Ropovik, 2015), when it is possible

to empirically analyze the impact of sample size on the chi-square statistic. We therefore

estimated the impact of sample size on chi-square in the present study: we repeated the

analysis with the baseline model in a subset of our sample. The subsample was generated by

randomly drawing 10% of applicants out of each group (with replacement) resulting in

sample sizes around $N = 300$ for each stratum, which is the usual recommendation to perform

such analyses. Only for the first group, the complete sample was employed because of the

small sample size. To minimize the impact of sampling error, we conducted the sampling

procedure 1,000 times, analyzed the baseline model each time and computed the mean of the

1,000 chi-square estimates. A comparison of this mean chi-square value with the chi-square

value in the complete sample allows an estimation of the impact of sample size on chi-square.

All models were nested models with increasing constraints. Therefore, these

constrained models were assessed using a direct model comparison to the less restricted

model. A model was determined to be invariant when the difference in the comparative fit

index (ΔCFI) was smaller or equal to .01 (Cheung & Rensvold, 2002; Kim, Cao, Wang, &

Nguyen, 2017).

5. Results

5.1. Descriptive analyses

Figure 2 shows how often the training modules for the cognitive ability tests were

actually used. Aggregated across the six cognitive domains, 10% of all candidates reported a

mean training level of 20 runs, thereby following the recommendation exactly. In contrast,

75% reported a lower level of training and 15% a higher one. As Table 3 illustrates, most

modules were practiced 14-15 times on average. The module for selective attention was used

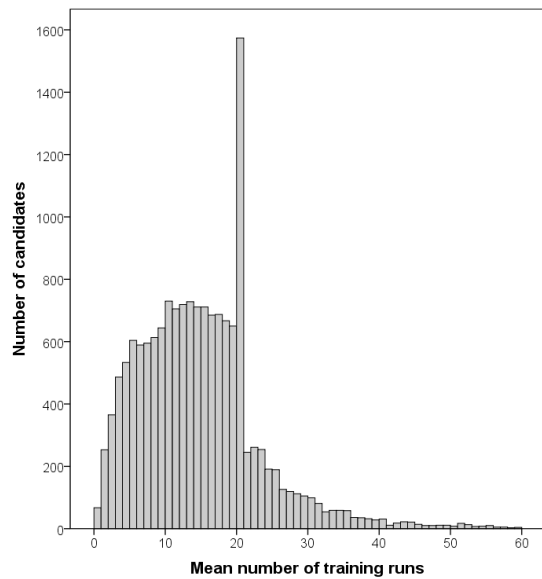less often and the module for visual perception speed was used more often.

Figure 2. Frequency distribution of the mean number of computer-based training runs across 6 ability measures, for display purposes rounded to integer values. *N* = 15,752.
[single column fitting image]

Table 3

Descriptive statistics for the number of computer-based training runs and performance in ability tests

	Training runs	Test performance	
	M (*SD*)	*M* (*SD*)	$r_{\text{Training,Test}}$
Selective attention	12.68 (8.49)	5.18 (1.79)	.32
Visual perception speed	17.16 (11.64)	5.22 (1.87)	.50
Auditory memory	14.73 (10.16)	5.33 (1.96)	.37
Visual memory	14.04 (9.96)	5.18 (2.07)	.36
Mental rotation	14.34 (9.93)	5.65 (2.22)	.37
Spatial visualization	14.30 (9.51)	4.91 (1.85)	.39
Knowledge in physics	-	4.90 (2.13)	-
Mechanical comprehension	-	4.63 (1.97)	-
Psychomotor coordination	-	4.72 (2.00)	-
Multiple task coordination	-	4.96 (1.91)	-

Note. For each measure the mean number of training runs and the mean stanine score of test performance is shown, together with the Spearman correlation of both variables. For the latter 4 measures no data for training quantity were available due to a different preparation concept. Due to the large sample size, indications of statistical significance for correlation coefficients are omitted. *N* = 15,752.

Table 3 also shows the performance data for all computer-based tests in stanines with

M = 5 and *SD* = 2. The mean test scores and the respective standard deviations measured in

our sample were comparable to the normative group, with slightly better performance than

the norm average of $M = 5$ in measures where training modules were offered in advance, and

a slightly lower performance than the norm in the others.

   For the six measures of cognitive abilities, the relationship between the number of

training runs and test performance was analyzed. As a visual inspection indicated that it was a

non-linear, monotonic relationship, we performed the analyses using Spearman's rank order

correlation. In contrast to the Pearson product-moment correlation, Spearman's coefficient

evaluates the monotonic relation between two variables and not the linear. As Table 3 shows,

there were substantial correlations between training runs and test performance. The

correlation coefficients ranged from r = .32 (selective attention) to r = .50 (visual perception

speed), with a mean correlation of $M = .39$ (the mean correlation was computed by

transforming the correlation coefficients to Fisher's Z values and back-transforming the mean

Z value). The more often a training module had been practiced on average, the higher was the

achieved test result. It must be noted, however, that higher average training scores were also

associated with higher standard deviations, so that the pattern of correlations between training

and test performance may be mediated by the variability in training runs. Figure 3 further

illustrates the relationship between the number of training runs and test performance. When

aggregated across the six cognitive ability measures, there was a non-linear relationship

between the number of training runs and test performance. Generally, more training predicted

on average better performance. However, the training gains became smaller with additional

training amounts. This pattern was also present when data were analyzed for each measure
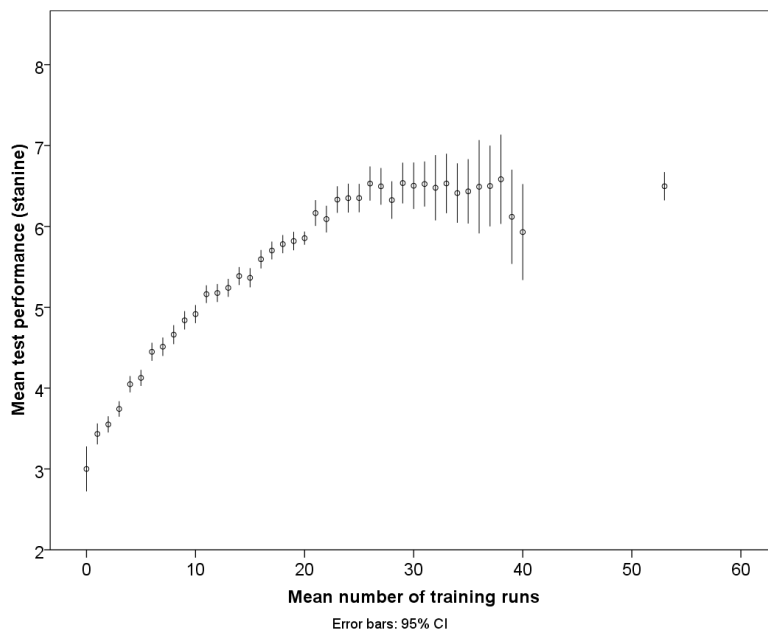
separately.

Figure 3. Relation between the mean number of computer-based training runs and mean test performance. X axis: mean number of training runs across 6 ability measures, for display purposes rounded to integer values; y axis: mean stanine scores aggregated across 6 ability tests, corresponding to the 6 training modules. Error bars indicate 95% confidence intervals. Due to small sample sizes with more than 40 training runs and increasingly larger confidence intervals, applicants with on average more than 40 training runs have been aggregated (only for display purposes; $n = 262$, $M = 53$ training runs). $N = 15,752$; the data point with the smallest sample size is at 39 training runs with $n = 28$.
[1-column fitting image]

5.2. Confirmatory factor analyses

The ability scores were tested across different levels of training for measurement and

structural invariance. The sequence of increasingly stringent models started with the

configural invariance model which imposes no parameter constraints across groups. As Table

4 shows, the fit of the configural invariance model was acceptable, $\chi^2(df = 192) = 2,396.23$, p

$< .001$, CFI $= .97$, RMSEA $= .07$, SRMR $= .03$. Imposing restrictions between groups also

resulted in acceptable model fit statistics and also the CFI differences between models were

acceptable: the metric invariance model (ΔCFI $= .001$), scalar invariance model (ΔCFI $=$

.003), residual invariance model (ΔCFI $= .003$), invariant factor variances model (ΔCFI $=$

.004), and the structural invariance model (ΔCFI $= .001$). Thus, the factorial structure of the

ability measurements remained constant across different levels of computer-based training,

supporting hypothesis 1.

Table 4

Goodness of fit for models of invariance across different levels of computer-based training

Model	χ^2 (*df*)	CFI	RMSEA (90% CI)	SRMR	Model comparison	ΔCFI	Decision
Configural invariance	2,396.23 (192)	.970	.066 (.064-.069)	.030	---	---	Accept
Metric invariance	2,552.27 (227)	.969	.062 (.060-.065)	.035	configural	.001	Accept
Scalar invariance	2,811.60 (262)	.966	.061 (.059-.063)	.037	metric	.003	Accept
Residual invariance	3,019.40 (312)	.963	.057 (.056-.059)	.038	scalar	.003	Accept
Invariant factor variances	3,394.23 (327)	.959	.060 (.058-.062)	.087	residual	.004	Accept
Structural invariance	3,438.54 (342)	.958	.059 (.057-.061)	.087	factor	.001	Accept

Note. Acceptance criterion for nested models: ΔCFI ≤ .01 (Cheung & Rensvold, 2002). CFI = comparative fit index, RMSEA = root mean square error of approximation, SRMR = standardized root mean square residual. *N* = 15,752 (see Table 1 for individual group sizes).

As outlined in the Methods section, a significant chi-square value is not a reliable

indicator of model fit in very large samples. To estimate the impact of sample size on chi-

square in the present study, we repeated the analysis with the finally accepted model (i.e., the

structural invariance model) in subsets of our sample. Mean chi-square in the subsamples was

$\chi^2(df = 342, N = 1,629) = 691.29$. While still statistically significant, there was a large drop in

the value of chi-square, indicating that it was considerably influenced by sample size.

Since measurement invariance across the different amounts of training was supported,

this also supported the hypotheses of a constant relationship between the ability constructs

and perceptual speed (hypothesis 2a) and between the ability constructs and psychomotor

coordination (hypothesis 2b). To specifically assess the importance of perceptual speed, a

modified version of the metric invariance model was analyzed where only the loadings of

perceptual speed on the latent cognitive ability factor was released, $\chi^2(df = 222) = 2,542.31$, $p < .001$, CFI = .97, RMSEA = .06, SRMR = .04. However, a direct model comparison with the metric invariance model showed no significant difference between the two models, $\Delta\chi^2(df = 5, N = 15,752) = 9.96$, $p = .076$. This implies that the liberalized, less parsimonious model, allowing different loadings between groups, did not result in a significantly better fit. It can be concluded that the importance of perceptual speed remained constant across different amounts of training. Hypothesis 2a was supported. To specifically evaluate the importance of psychomotor coordination, again a modified version of the metric invariance model was analyzed. In this case psychomotor coordination was allowed to load on the latent cognitive ability factor, $\chi^2(df = 221) = 2,549.09$, $p < .001$, CFI = .97, RMSEA = .06, SRMR = .04. Again, a direct model comparison showed no significant difference between the two models, $\Delta\chi^2(df = 6, N = 15,752) = 3.18$, $p = .786$, suggesting that the importance of psychomotor coordination remained constant across different training quantities, supporting hypothesis 2b.

6. Discussion

With the growing use of computer-based diagnostics, especially in applied contexts, the question of good and fair preparation for applicants has become increasingly crucial. Preparation for ability tests has become an industry in many selection contexts and the financial resources of the applicant and differences in quantity and quality of test preparation constitute growing sources of variance and unfairness. Our approach to cope with this challenge was to offer freely available computer-based training modules to all applicants. The present study showed that there were training effects consistent with previously published research, but most importantly, the structure of the tests was not altered by offering free training to all applicants. The analyses for measurement and structural invariance indicated that there was no change in the factorial structure of the ability measures. With regard to our specific hypotheses, the invariance analysis showed that increasing levels of training did not

alter the importance of perceptual speed and psychomotor coordination within the factorial

structure. With respect to Ackermann's theory (1988), this finding is interpreted as evidence

for the fact that training did not alter the measured constructs from rather broad abilities to

task-specific skills. This can be attributed to the way the ability tests of the present study

were designed: they were characterized by an inconsistent structure, i.e. the rules for item

processing changed constantly during the test. This inconsistency impeded the process of

automation and required continuous active information processing. Therefore, even after

intense practice, the content abilities (Ackerman, 1988) remained the main factor for solving

the test items and hence, the structural validity of the tests was not affected.

Previous studies have already analyzed the measurement invariance of cognitive

ability tests in the context of practice and retest effects. However, as a result of different

criteria for defining the groups, these are not directly comparable to the present study. For

example, previous studies analyzed invariance across classes of training prior to admission

testing (Arendasy et al., 2016), practice with different cognitive tasks between repeated

intelligence measurements (Estrada, Ferrer, Abad, Román, & Colom, 2015), different

methods used to construct alternate test forms (Arendasy & Sommer, 2013), or authors

analyzed invariance across different measurement occasions (Arendasy & Sommer, 2017;

Freund & Holling, 2011; Lievens et al., 2007; Reeve & Lam, 2005; Sommer, Arendasy, &

Schützhofer, 2017). To our knowledge, the present study is the first that analyzes

measurement and structural invariance across different amounts of test-specific training. As

most of the previous invariance studies, our invariance analyses were conducted within a

multi-group framework. Recently, moderated nonlinear factor analysis was proposed as a

more general approach (Bauer, 2017): it allows investigating measurement invariance also for

continuous variables which could be used in future research.

Additionally, we found that although there were instructions given for computer-based training in the present study, applicants did not always follow them, resulting in a large variability in the use of the training modules. The reasons for the large differences in training quantity may be diverse: individual differences in motivation, time resources, beliefs about the effectiveness of training or correctness of self-evaluations (for relevant factors in commercial coaching programmes, see Ryan, Ployhart, Greguras, & Schmit, 1998). Therefore, when psychologists decide to offer computer-based training to all applicants, they must decide how to cope with these possible influences. One strategy could be to allow applicants to participate in the examination only if they confirm having trained up to a specified level. This could enhance construct validity since the measurements are less biased by differences in training and hence, potential differences in motivation, time resources, or correctness of self-evaluations. However, it should also be considered that such differences may provide diagnostically relevant information. Moreover, to the extent that these differences meet requirements for the later job, the criterion-related validity of measurements will be enhanced if applicants are allowed to participate in the examination irrespective of their actual training level. In this case, it is mandatory to offer the training software to all applicants, with sufficient time for an adequate test preparation. In addition, institutions have to underline the importance of training to all applicants, otherwise the risk that applicants only fail the examination due to insufficient training will be unacceptably large. Such false negative decisions are probable since in most cases the introduction of training software necessitates the adjustment of test norms—which become stricter as a result of the training effects. In particular, if the number of potentially suitable applicants is rather small, the costs of false negative decisions are high. Taken together, there is some investment required with the introduction of computer-based training but it ensures that training and the resulting score gains are not restricted to applicants with high financial resources.

Consistent with studies on practice effects and learning curves, we found a positive, non-linear relationship between the quantity of computer-based training and cognitive performance (Bartels, Wegrzyn, Wiedl, Ackermann, & Ehrenreich, 2010; Donner & Hardy, 2015). Such a relation was also reported by studies that used the time spent on training and not the number of training runs (cf. Hausknecht et al., 2007), which is plausible since the time spent on training and the number of training runs should be highly correlated. As discussed in several lines of research, the relationship between training and cognitive performance is mainly based on familiarization with the item format and an increase in test-specific skills (for an overview of the causes of retest and practice effects see Randall & Villado, 2017; Van Iddekinge & Arnold, 2017). Recent evidence supported the hypothesis that score gains after repeated testing are due to refinements in the solution strategies of subjects (Arendasy & Sommer, 2017; Hayes, Petrov, & Sederberg, 2015). As Arendasy and Sommer (2017) point out, when subjects repeatedly conduct an ability test, information on speed and accuracy of the solution strategy and salient item design characteristics are stored in working memory. With further retests, the cognitive schema becomes more automatized and hence more working memory resources become available. Depending on the nature of the cognitive ability analyzed, such an automation process may proceed at different speeds, with for example simple speed tasks reaching the plateau faster than memory or reasoning tasks (Scharfen, Jansen, & Holling, in press; Scharfen et al., 2018).

A limitation of the present study is that the number of training runs was not experimentally manipulated and not directly monitored but only reported by each applicant. Therefore, it cannot be excluded that the training data were biased by record inaccuracies or socially desirable behavior. For example, we do not know whether the participants actually adhered to the suggestion or whether the spike after run 20 in figure 3 could be due to social desirability. Furthermore, it is possible that some applicants had used commercial preparation

methods in addition to our training software. However, the relationship between training data

and test performance, which is in line with theoretical expectations based on Ebbinghaus'

learning curves (cf. Figure 1) suggest that such influences are—at least on average—of only

minor importance. Moreover, the training guidance with recommendations and the record

template, together with the upcoming high-stakes setting, are likely to have increased the

reliability of the training records. It would be desirable to more closely monitor the training

activities of the applicants, for example by tracking the usage of the software. However, in

this case the monitoring process should be made transparent to the user to ensure data

protection and to prevent negative reactions such as reactance or enhanced socially desirable

behavior (cf. Ketelaar & van Balen, 2018).

Particularly in times of internet testing and the growing (online) availability of

information about tests, to be reliable and fair, psychological diagnostics has to react. Our

results suggest that free computer-based training is a possible way to react to today's

challenges without affecting the measurement quality in diagnostic decision making and tests

for measurement invariance are an efficient way to screen for such potential biases. However,

offering training software to all applicants is certainly not the optimal strategy in every

applied context. For example, if sufficient training cannot be implemented due to insufficient

individual prerequisites (such as in neuropsychology or psychiatry) or contextual conditions

(e.g., short time lags between registration and assessment), this training concept is not

appropriate. Similarly, if the ability tests have a rather simple structure which makes them

vulnerable to skill development after practice, other strategies may be more appropriate. In

these cases, the application of alternative ability tests and test versions should be preferred.

Alternatively, the test-retest interval may be extended (Scharfen et al., in press). For

personnel selection contexts, however, offering computer-based training to all subjects offers

a powerful tool to ensure sufficient fairness of the diagnostic process.

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