Intelligence 69 (2018) 37–49

Contents lists available at ScienceDirect

Intelligence

journal homepage: www.elsevier.com/locate/intell

Dedifferentiation and differentiation of intelligence in adults across age and years of education☆

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ARTICLE INFO

Keywords:
Local structural equation models
Differentiation-dedifferentiation
Intelligence
Measurement invariance
Age
Spearman's law of diminishing returns

ABSTRACT

The extent that the structure of cognitive abilities changes across the lifespan or across ability levels is an ongoing debate in intelligence research. The differentiation-dedifferentiation theory states that cognitive abilities differentiate until the beginning of maturity, after which relations increase or dedifferentiate until late adulthood. Spearman's law of diminishing returns proposes that cognitive abilities are more differentiated at higher ability levels. However, the evidence for ability differentiation and age dedifferentiation, in particular, is mixed. A prerequisite for the evaluation of dedifferentiation processes, expressed as changes in ability factor correlations, is the invariance of intelligence across age. However, a strong interpretation of the dedifferentiation hypothesis states that changes in model parameters, such as factor loadings and residual variances, can also be indicative of dedifferentiation. Traditional statistical tools for testing measurement invariance are not feasible for studying parameter changes over a continuous context variable, such as age. However, a recently developed non-parametric method, Local Structural Equation Modeling (LSEM), closes this gap. LSEM is a powerful and versatile method for studying structural changes; it is an improvement over competing methods, because it avoids artificial categorization of a moderator that is continuous in nature and also renounces the determination of a priori parameter functions. Using cross-sectional data from the standardization sample of the Woodcock-Johnson IV Intelligence Test Battery, we present an application and extension of the LSEM approach to accommodate two moderator variables. Specifically, we studied measurement invariance across two context variables, age and years of education, in models testing the unique moderating effect of each, and in a model examining their combined effects. We found no significant moderating effects of age and no effects of years of education on the relation between fluid and crystallized intelligence. Moreover, an interaction of age and years of education with respect to model parameter change cannot be supported.

1. Introduction

For more than a century, the structure and stability of cognitive abilities have been a major theme in intelligence research (e.g., Wilhelm & Engle, 2004). In Cattell's (extended) gf–gc-theory (Cattell, 1971; Horn & Noll, 1997), reasoning (i.e., fluid intelligence, gf) and declarative knowledge (i.e., crystallized intelligence, gc) are the most prominent factors. Gf is conceptualized as the decontextualized ability to solve abstract problems, while gc represents a person's knowledge gained during life by acculturation and learning (Cattell, 1971). In a pivotal study, Carroll (1993) reanalyzed 461 data sets by employing exploratory factor analysis with oblique rotation to higher-order factor matrices, resulting in the three-stratum theory of cognitive abilities. A synthesis of Cattell's and Carroll's models has led to the *Cattell-Horn-Carroll (CHC) model* (McGrew, 2005, 2009), which constitutes a preliminary endpoint in theory building.

In the present study, we examined age- and education-related changes in the covariance structure of gf and gc. Until now, the influence of covariates has mostly been investigated independently (see also Tucker-Drob, 2009), which is especially problematic in lieu of inconsistent findings on the relation of education and age on cognitive decline in late adulthood (e.g., Anstey & Christensen, 2000). To close this gap in research, we studied the combined influence of age and education on the structure of cognitive abilities.

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https://doi.org/10.1016/j.intell.2018.04.003
Received 31 May 2017; Received in revised form 27 March 2018; Accepted 11 April 2018

1.1. Age-related changes in the structure of intelligence

A prominent theory about the structural development of cognitive abilities claims neointegration or dedifferentiation in old age (Baltes, Staudinger, & Lindenberger, 1999). According to this *dedifferentiation hypothesis*, the g-factor explains more variance with increasing age. With respect to the gf-gc model, an increasing correlation between the two factors across age could be seen as support for the dedifferentiation theory. The reason for the lower complexity of the structure of intelligence in old age is ascribed to neurobiological constraints on cognitive functioning (Baltes et al., 1999). In a refinement of the original theory, two types of dedifferentiation are assumed: dynamic and non-dynamic dedifferentiation (Lövdén & Lindenberger, 2005). The *dynamic differentiation theory* states that the development of cognitive abilities in old age is mainly influenced by common sources, resulting in higher correlations between different cognitive abilities. For example, the decline in gf limits gc expression and accumulation. In contrast, the *non-dynamic dedifferentiation theory* states that changes in different cognitive abilities are due to a common developmental cause which influences all cognitive abilities with an invariant strength with increasing age. Thus, an increase in the correlations across abilities is driven by comparative age trends for the different abilities.

Several empirical studies have examined age-related changes in the structure of intelligence (Zelinski & Lewis, 2003). We present a limited overview in Table 1, focusing on studies with adult samples and highlighting the different methodological approaches. The empirical results are inconsistent. On one hand, there is evidence supporting the dedifferentiation of cognitive abilities in adults (e.g., de Frias, Lövdén, Lindenberger, & Nilsson, 2007; Hertzog, Dixon, Hultsch, & MacDonald, 2003; Hülür, Ram, Willis, Schaie, & Gerstof, 2015; Li et al., 2004). On the other hand, there is even more empirical evidence against the dedifferentiation theory (e.g., Batterham, Christensen, & Mackinnon, 2011; Bickley, Keith, & Wolfle, 1995; Hildebrandt, Wilhelm, & Robitzsch, 2009; Juan-Espinosa et al., 2002; Niileksela, Reynolds, & Kaufman, 2013; Taub, McGrew, & Witta, 2004; Tucker-Drob, 2009; Tucker-Drob & Salthouse, 2008; Whitley et al., 2016; Zelinski & Lewis, 2003). In the same vein, the relation between gf and gc over age is inconsistent. Some studies found an increasing correlation between the two factors in old age, which is in line with the dedifferentiation theory (e.g., Hayslip & Sterns, 1979; Li et al., 2004). In contrast, some studies found the correlation between gf and gc was smaller for the elderly in comparison to younger adults (e.g., Cunningham, Clayton, & Overton, 1975; Tucker-Drob & Salthouse, 2008).

Overall, when the sample size is sufficient and age groups are narrow, analysis with Multi-Group Confirmatory Factor Analysis (MGCFA, see 1.3 for a description), and methods using age as a continuous variable support invariance of cognitive abilities across age. However, the results of these studies should be interpreted with caution because of limitations to their study designs and statistical methods used. In order to conduct a decent test of dedifferentiation, the study should meet following criteria. First, the age range in the examined sample should be large enough to reasonably expect dedifferentiation effects. This claim requires the inclusion of persons of old age (> 60). Second, since age is a naturally continuous variable, it should be treated as such when used as a context variable. Third, indicators reflecting more than one ability should also be examined for changes in their associations over age. Fourth, one needs to account for the potentially differing reliability of indicators over age, for example by examining correlations between latent variables instead of manifest variables. Fifth, irrespective of the methodological approach, a sufficiently heterogeneous sample of an adequate size is necessary to produce reliable and generalizable results. Finally, Hofer, Flaherty, and Hoffman (2006) point to the possibility of mean-induced association in cross-sectional data, which means that ability test correlations are inflated due to age-

Table 1
Overview of studies examining age-related dedifferentiation of intelligence.

Study	*N*		Age range		Design	Model		Statistical method	
Baltes et al. (1980)	109	(X)	60–89	(✓)	Cross-sectional	Gf-gc model	(✓)	CFA (variance accounted for by g-factor)	(X)
de Frias et al. (2007)	1000	(✓)	35–80	(✓)	Longitudinal (3 occasions over 10 years)	Correlated factor model	(✓)	Latent growth modeling	(X)
Hayslip and Sterns (1979)	162	(X)	17–26, 39–51, 59–76	(X)	Cross-sectional	Gf-gc model	(✓)	Correlation of manifest composite scores	(X)
Hertzog et al. (2003)	303		61–91	(✓)	Longitudinal (6 years)	Correlated factor model	(✓)	Latent change model Age as a covariate	(X)
Hülür, Ram, Willis, et al. (2015)	419	(✓)	22–106	(✓)	Longitudinal (up to 49 years)		(✓)	Multilevel modeling	(X)
Li et al. (2004)	291	(X)	6–89	(✓)	Cross-sectional	Gf-gc model	(✓)	Correlation of manifest composite scores Principle component analysis	(X)
Batterham et al. (2011)	687	(✓)	70–97	(✓)	Longitudinal	g-factor model	(X)	MFA	(X)
Bickley et al. (1995)	2201	(✓)	6–79		Cross-sectional	Three-Stratum		MGCFA	
Cunningham et al. (1975)	75	(X)	19.05 (*SD* = 1.36), 60–79	(X)	Cross-sectional	Gf-gc model	(✓)	Correlation of manifest composite scores	(X)
Hildebrandt et al. (2009)	448	(✓)	18–82	(✓)	Cross-sectional	g-factor model	(X)	MGCFA, LMS, LSEM	(✓)
Juan-Espinosa et al. (2002)	1369	(✓)	16–94	(✓)	Cross-sectional	Higher order g-factor model	(✓)	Exploratory, factor analysis, MGCFA	(X)
Niileksela et al. (2013)	2200	(✓)	16–90	(✓)	Cross-sectional	CHC model	(✓)	MGCFA	(X)
Taub et al. (2004)	2450	(✓)	16–89	(✓)	Cross-sectional	Higher order g-factor	(✓)	MGCFA	(X)
Tucker-Drob (2009)	6273	(✓)	4–101	(✓)	Cross-sectional	CHC model		MFA	(X)
Tucker-Drob and Salthouse (2008)	2227	(✓)	24–91	(✓)	Cross-sectional	g-factor and correlated factor model	(✓)	CFA (variance accounted for by g-factor), MGCFA, MFA	(X)
Whitley et al. (2016)	49,258	(✓)	16–100	(✓)	Cross-sectional	g-factor model	(X)	MFA, LSEM	(✓)
Zelinski and Lewis (2003)	289	(X)	30–97	(✓)	Longitudinal	Correlated factor model	(✓)	MGCFA	(X)

Note. CFA = Confirmatory Factor Analysis, CHC model = Cattell-Horn-Carroll model, gc = crystallized intelligence, gf = fluid intelligence, MFA = Moderated Factor Analysis, MGCFA = Multi-Group Confirmatory Factor Analysis, LSEM = Local Structural Equation Models; brackets indicate if defined quality criteria are (✓) or are not (X) met: sufficient sample size with an even distribution across the age range and a sufficient number of participants per estimated parameter, age range includes old persons (> 60) and allows for continuous age examination, model includes associations between different cognitive abilities, method treats age as a continuous variable and uses narrow-age cohorts.