Carmen Flores-Mendoza · Rubén Ardila
Ricardo Rosas · María Emilia Lucio
Miguel Gallegos · Norma Reátegui Colareta

Intelligence Measurement and School Performance in Latin America

A Report of the Study of Latin American Intelligence Project

Springer

Intelligence Measurement and School Performance in Latin America

Carmen Flores-Mendoza • Rubén Ardila
Ricardo Rosas • María Emilia Lucio
Miguel Gallegos • Norma Reátegui Colareta

Intelligence Measurement and School Performance in Latin America

A Report of the Study of Latin American Intelligence Project

Springer

Carmen Flores-Mendoza
Department of Psychology
Federal University of Minas Gerais
Psychology Institute
Belo Horizonte, Minas Gerais, Brazil

Ricardo Rosas
School of Psychology
Pontifical Catholic University of Chile
Santiago, Chile

Miguel Gallegos
Faculty of Psychology
National University of Rosario
Rosario, Argentina

Rubén Ardila
Department of Psychology
National University of Colombia
Bogota, Colombia

María Emilia Lucio
Mental Health and Diagnosis Program
Faculty of Psychology
National Autonomous University of Mexico
Mexico City, Distrito Federal, Mexico

Norma Reátegui Colareta
Faculty of Humanities
San Ignacio de Loyola University
Lima, Lima y Callao, Peru

ISBN 978-3-319-89974-9 ISBN 978-3-319-89975-6 (eBook)
https://doi.org/10.1007/978-3-319-89975-6

Library of Congress Control Number: 201893955

Printed on acid-free paper

This Springer imprint is published by the registered company Springer International Publishing AG part of Springer Nature.
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

In memory of
Professor Earl B. Hunt (1933–2016), who always cared about the human beings behind the numbers, especially those living in vulnerable contexts.

Preface

Before we explain why this book was written, allow us to provide four interesting examples of recent social facts, unfortunately very replicated in the history of the Latin-American region:

1. In 2014, a small mining village began to benefit from the high commodity prices. Despite the apparent financial improvements, the village had no drinking water, sewage treatment, medical care, or proper housing. For this reason, there were high rates of malnutrition and infant mortality. The village authorities decided to build a theme park dedicated to honoring dinosaurs instead of solving basic community problems. The park cost nearly US$ 1,000,000.00. The mayor justified this project by saying: “Dinosaurs are part of history; children need to know what happened, how these animals lived, how they became extinct.” One year later, the theme park was totally abandoned.
2. At the conclusion of 2013, a Latin American president decided to create the role of “The Vice-Minister for the Paramount Social Happiness” (direct translation). Five years later, the country was engulfed in an unprecedented economic crisis, the highest inflation rate in the world (5000%), a crumbling public healthcare system (no medicine available in hospital pharmacies), and food shortages in the supermarkets. This crisis has driven 10% of the population to seek refuge in neighboring countries, making it the largest exodus ever seen in the Latin America region.
3. In 2016, during legislative assembly, which was voting for the impeachment of the President, the behavior of the lawmakers from the lower house greatly alarmed the population. The lawmakers screamed, became physically aggressive, and demonstrated inappropriate conduct (chanting anthems or talking in parodies). These behaviors were reported as “circus stunts and behavior” by the national and international media.
4. At the beginning of 2012, the prestigious magazine The Economist denounced false economic data of a South American country. The government of this country had offered continuous misreported prices, and false inflation figures, that swindled holders of inflation-linked bonds.

These social facts indicate that Latin American authorities sometimes make questionable decisions and demonstrate inabilities in identifying and acting on the needs of the population they represent. However, bad political decisions (or unprepared politicians) can occur in any country: developing or developed. The difference is that in developing countries, such as those found in Latin America, politically bad decisions (or errors) are more frequent and more devastating to the progress of these nations.

It would be tempting and easy to blame corrupt politicians for the poor socioeconomic indicators of Latin American countries, or to indicate other reasons (economic, sociological, historical, or cultural) that contribute to the poor results. However, here we present another point of view. We consider that authorities, political leaders, professionals, workers, entrepreneurs, educators, scientists, etc. are part of the human capital available within any country. Human capital that deserves to be studied and understood. Not only from the point of view of education, which is a factor extensively studied, but also from a psychological variable, strongly related to school performance, commonly known as Intelligence.

This point of view is not new. After the publication of the book "IQ and Wealth of Nations" in 2002, authored by the British psychologist Richard Lynn and the Finland economist Tatu Vanhanen, researchers have documented the strong relationship between national intelligence and Gross National Income, national school performance, rates of infant mortality, life expectancy, and diverse important social index.

The national IQ scores were explained based on a mix of varied methodological problems, such as small sample or unrepresentative sample sizes, different kinds of tests, assessments conducted during different years, and unweighted arithmetic means of neighboring countries, in cases of missing data. To some extent, these problems were overcome by incorporating results from international student assessments, as a proxy measure of intelligence. Due to the social consequences of the national intelligence, it is necessary to achieve evidence regarding the levels and specific skills that are present in our population, administering the same cognitive measures during the same period of time.

This book presents the results from the project entitled, "Study of Latin-American Intelligence" (SLATINT), conducted by a team of Latin American researchers. A cognitive battery, a short version of PISA test (school measure), and a socioeconomic questionnaire were administered to almost 4000 students from six Latin American cities (Belo Horizonte, Bogota, Lima, México city, Rosario, Santiago) and one European city (Madrid) during the period 2007–2011 (80% in 2008–2009). Therefore, it is a design closer to crosscultural studies.

We hope that the information contained in this book can contribute to a better understanding the cognitive skills present in Latin American human capital, and, at the same time, we hope this information can allows the developing of better long-term public policies that effectively strength these skills.

Belo Horizonte, 2018 Carmen Flores-Mendoza

Acknowledgements

Special thanks are given to the psychologists named below for their collaboration during the data collection process for the SLATINT Project:

Gislene Clemente Vilela Câmara (Pontifícia Universidade Católica de Minas, Brazil), Wilma M. Guimarães Lopes (Universidade FUMEC, Brazil), Ana P. Carvalho Pereira Passos (Pontifícia Universidade Católica de Minas, Brazil), Ana Maria Valladão Pires Gama (Pontifícia Universidade Católica de Minas, Brazil), Viviane de Oliveira Baumgartl (Pontifícia Universidade Católica de Minas, Brazil), Larissa Assunção Rodrigues (Universidade Federal de Minas Gerais, Brazil), Marilourdes Barbosa (Universidade FUMEC, Brazil), Oscar Galindo (Universidad de Los Andes, Colombia), Omar Fernando Cortés (Universidad Católica de Colombia), Andres Burga León (Universidad de Lima and Ministry of Education, Peru), and Karla Leiva Guerrero (Psychologist).

Special acknowledgment is made to the professors Roberto Colom (Universidad Autónoma de Madrid, Spain) and Heiner Rindermann (Technische Universitat Chemnitz, Germany), who showed enthusiasm about the SLATINT Project and offered valuable advice to our team.

Contents

1 Introduction 1
- 1.1 The Latin-America Region 1
- 1.2 The SLATINT Project 4
  - 1.2.1 Participant Countries 4
  - 1.2.2 Design Adjustments 5
  - 1.2.3 Final Design of the SLATINT Project 7
  - 1.2.4 Financing and Logistics 8
  - 1.2.5 Final Sample 8
- 1.3 Organization of this Book 8
- References 10

2 Cognitive Factor Structure: The *g* Factor 13
- 2.1 The *g* Factor 13
- 2.2 The *g* Factor in Latin American Samples 15
  - 2.2.1 Correlation Matrices 17
  - 2.2.2 Determining the Factor Structure of *g* 18
  - 2.2.3 Confirmation of Model in Individual Samples 21
- 2.3 Conclusion 22
- References 22

3 Education, SES, and Intelligence 25
- 3.1 Introduction 25
- 3.2 Intelligence and Education: Lessons from Differential Psychology 26
- 3.3 Education in Latin America: How Prepared Is the Region for this New Era? 29
- 3.4 Education and Intelligence: Results from the SLATINT Project 29
- 3.5 Conclusion 39
- References 39

4 Intelligence, Problem Solving, and Creativity 43
4.1 Problem Solving. 43
4.1.1 High and Low Problem Solving Ability Based on the *g* Factor 46
4.1.2 Do Good Problem Solvers Make Different Types of Errors Compared to Poor Problem Solvers? 50
4.2 Creativity 56
4.3 Conclusion 59
References. 60

5 Cognitive Sex Differences 63
5.1 Variability Hypothesis 64
5.1.1 The Variability Hypothesis in Latin American Studies. 65
5.1.2 Testing the Variability Hypothesis with the Sample from the SLATINT Project 67
5.2 Developmental Theory of Sex Differences 69
5.3 Sex Differences in Specific Abilities 71
5.3.1 Latin American Sex Differences in Univariate Analysis 71
5.3.2 Latin American Sex Differences in Multivariate Analysis. 73
5.4 Sex Differences at *g* Level 73
5.5 Conclusion 74
References. 75

6 Intelligence, Latin America, and Human Capital 79
6.1 Human Capital 80
6.2 Wealth of Nations, Jobs, and Distribution of Human Capital 80
6.3 Intelligence of Nations. 83
6.4 The SLATINT Project 87
6.4.1 Samples and Quality 88
6.4.2 The SPM Test. 90
6.4.3 Estimating the "Greenwich-IQ". 93
6.5 Immigrants 99
6.6 Parent Occupation and Cognitive Performance of Their Children 102
6.7 Internet 103
6.8 Birth Order. 104
6.9 Human Capital in Latin America and Spain 106
6.9.1 Intelligence. 107
6.9.2 School Achievement 107
6.9.3 Solving Problems. 108
6.10 Conclusion 108
References. 109

7 Final Words 113
References 117

Appendix: Complementary Data 119

Index 121

Chapter 1
Introduction

Abstract Intelligence at an individual and national level is discussed. The lack of studies in the Latin American context justified the project named SLATINT (Study of the Latin American Intelligence). Here the project is described from its conception to the achieved design (sampling and psychological measures used).

1.1 The Latin-America Region

The term "Latin America" was first used in 1856 by the Colombian journalist José Maria Torres Caicedo to distinguish Latin nations from Saxon nations (Farret & Pinto, 2011). Latin America is a region of the American continent that is composed of 20 independent nations. This region possesses a territorial extension of 20 million square kilometers (13.5% of the total world territory). In 2015, the Latin American region had approximately 620 million people (66% speaking Spanish, 33% speaking Portuguese, and 1% speaking French). Of the 620 million people, 67% were Catholics. At the time of the survey, Latin America was home to the second largest population of young people in the world.

Following their independence from the Spanish and Portuguese crown during the nineteenth century, the history of the Latin American nations is characterized by several within-country political battles, revolts, and military coups, resulting in short periods of alternating rule of law. In most instances, the primary cause for Latin America's political instability was the traditional social hierarchy (strongly associated with race) and high socioeconomic inequality. Unfortunately, these two factors have remained constant for almost the same period of time within and between nations (Donghi, 2005). For example, between 1900 and 1950, Latin American nations with the largest population of European ancestry, such as Argentina and Chile, had the highest literacy rate (average of 65.5%) when compared to countries containing the largest population of indigenous or African ancestry, such as Peru, Mexico, or Brazil (average of 42.2%). The same trend is observed regarding income and life expectancy (Astorga, Bergés, & Fitzgerald, 2004).

However, at the end of the twentieth century, differences in social indicators between and within nations began to decline in the Latin American region. In 2000,

C. Flores-Mendoza et al., *Intelligence Measurement and School Performance in Latin America*, https://doi.org/10.1007/978-3-319-89975-6_1

Latin America achieved a literacy rate of 87% and life expectancy of 70 years (Astorga et al., 2004). Income, schooling, and life expectancy are important social indicators included in the Human Development Index (HDI). According to the Human Development Report of 2010 (PNUD, 2010), the Latin American region moved from a HDI of 0.58 in 1970 to HDI 0.77 in 2010 (32% improvement in 30 years). This change was mostly related to improvements in gross national income per capita, which grew from US$ 5900 to US$ 11,092 (data based on purchasing power parity of 2008 US dollars). Moreover, according to the report by the OECD (2016), poverty rates decreased from 0.521 in 1999 to 0.469 in 2015 (Economic Commission for Latin America and the Caribbean, 2017).

Despite the remarkable socioeconomic growth, Latin America continues to be under-prepared in terms of human capital, as shown by reports from the International School Assessment, such as the PISA test (Programme for International Student Assessment), a large-scale test sponsored by the Organisation for Economic Co-operation and Development (OECD). Since the first PISA test in 2000, results revealed that the majority of Latin American students attained a skill level in reading, science, and mathematics below that of students from countries with similar income levels (OECD, 2003, 2007, 2010, 2013). According to the OECD, good knowledge and the ability to extrapolate learned knowledge and apply it to novel situations are skills that are extremely necessary for a nation that is dealing with new challenges in modern society (OECD, 2013). If this concept is correct, Latin American countries are facing a big problem. According to the results of the 2012 PISA test, Asian countries had on average 36.9% of top performers in mathematics globally, as compared to Europe (13%) and Latin America (0.7%).

According to the concept of education encouraged by the PISA test creators, knowledge is evaluated along with its applicability to solve everyday situations. In this sense, the results of the PISA test would indicate that, despite continuous increases in average years of schooling, the problem-solving ability of Latin American nations has not increased. With regard to this bleak picture, a World Bank report (Cunningham, Acosta, & Muller, 2016) raised a controversial issue: Is it a problem based on lack of skills? For example, despite the GDP per capita of the Ukraine being 30% less than Colombia, 33% of Colombian adults had a level 1 in reading skills (basic level) while only 15% of Ukrainian adults had the same level. According to the World Forum Economic (WEF, 2016), a change of job or career demands new and more evolved work skills. In this sense, advanced cognitive functions, beyond personality characteristics, would be the skills most valued by the current labor market. Here, it is of interest to observe that the World Bank emphasized the role of socio-emotional skills for success at work; however, their data analysis (Table 1, page 4) showed that for the four Latin American countries studied (Bolivia, Colombia, El Salvador, and Peru), cognitive skills were more strongly associated with success at work than socio-emotional skills.

The role of cognitive abilities in school or work performance is well-understood in differential psychology, which is a part of psychology dedicated to studying the ways in which people differ from each other and the causes of these differences (Revelle, Wilt, & Condon, 2011). Cognitive ability is an alternative term to the traditional term "intelligence," as well as "general intellectual ability" or "*g* factor." Regardless of the word used to label intelligence, Detterman (book in preparation)[1] recommends that we take into consideration that we do not know what intelligence is, and different people (or researchers) can have diverse definitions of it. For instance, the two major academic discussions about what *intelligence* is (Sternberg & Detterman, 1986; Thurstone, 1921) resulted in the formation of a variety of concepts.

However, for the purpose of this book, we will use the term "intelligence" in the context of the meaning proposed by a team of 52 signatories and published in an editorial of the Intelligence Journal (Gottfredson, 1997; first publication in 1994 in the Wall Street Journal), and confirmed by other researchers (Neisser et al., 1996). According to these two groups, intelligence is a broad capacity, a very general ability for reasoning, planning, anticipating, and problem-solving abstract thinking, absorbing and understanding complex ideas, and learning from experience. This statement has been incorporated in recent textbooks (e.g., Hunt, 2010) and by several research papers dealing with the topic of intelligence.

The history of intelligence research and the creation of psychological tests are very strongly connected. It is not possible to ignore the fact that, after a century of research, the scientific understanding of intelligence is based on psychometric tests. Independent of its format (paper-and-pencil or computerized), cognitive psychological tests are a good predictor of life outcomes. In this sense, results have invariably indicated that intelligence is positively associated with school achievement (Gottfredson, 2002; Kuncel, Hezlett, & Ones, 2004; Neisser et al., 1996), work performance (Gottfredson, 2003, 2006), vocational interest (Gottfredson, 1999), and knowledge on current events (Beier & Ackerman, 2001, 2003, 2005). On the contrary, intelligence is negatively associated with psychiatric disorders (Walker, McConville, Hunter, Deary, & Whalley, 2002), crime (Hirschi & Hindelang, 1997; Lynam, Moffitt, & Stouthamer-Loeber, 1993), or general health problems (Geoff, Batty, & Deary, 2009). These results allow us to infer the ubiquity of intelligence in the life of human beings.

With such impressive results in the field of individual differences, investigators sought to determine whether intelligence could be a factor that could explain the differences in intelligence between countries. Effectively, the answer was revealed with the publication of the book, "IQ and the Wealth of Nations," written by the British psychologist Richard Lynn and the Finn political scientist Tatu Vanhanen, (Lynn & Vanhanen, 2002). This book is considered a source of inspiration and reference for several social, economic, and psychological crosscultural studies. Briefly, Lynn and Vanhanen estimated the mean IQ of 185 nations from published studies, where intelligence tests were administered to population samples. For 78% of the countries, IQ was derived from a single test, the Raven Progressives Matrices (SPM), a non-verbal reasoning test. In 2006 and 2012, Lynn and Vanhanen (2006, 2012) revised the first estimate of the world's average IQ. After some modest corrections for the incorporation of school performance and new cognitive perfor-

[1] Douglass Detterman is the founder of the scientific journal Intelligence.

mance data, the result actually remained the same: a correlation of 0.757 between country's average IQ and Gross Domestic Product (GDP) or 0.706 with Gross National Product (GNP), both values being statistically significant.

Beyond wealth (Dickerson, 2006; Jones & Schneider, 2006; Whetzel & McDaniel, 2006), a country's IQ is related to national differences in life expectancy (Kanazawa, 2006), rates of secondary education enrollment, illiteracy, agricultural employment (Barber, 2005), crime (Rushton & Templer, 2009), school achievement (Rindermann, 2007), production of technological knowledge (Gelade, 2008; Jones & Schneider, 2010), atheism (Lynn, Harvey, & Nyborg, 2009; Reeve, 2009), educational achievement (Lynn, Meisenberg, Mikk, & Williams, 2007; Lynn & Mikk, 2007), fertility rate (Reeve, 2009; Shatz, 2008), infant and maternal mortality rate (Reeve, 2009), HIV/AIDS rate (Rindermann & Meisenberg, 2009), and social inequality (Meisenberg, 2008). This impressive ubiquity of intelligence indicates the importance of assessing the mental abilities of a nation, i.e., the importance of the identification of both minimal and high-level skills that underlie the national development and general well-being.

Perhaps the most notorious relationship is between intelligence and school performance (Lynn et al., 2007; Lynn & Meisenberg, 2010). In this field, Rinderman (2007) combined the results of IQ tests and school performance tests, and extracted a strong g-factor, which represented the cognitive competence of each country. For this reason, the SLATINT Project was designed to understand the relationship between mental abilities and school performance in Latin American students. Last but not least, the SLATINT Project is a record of results that can be replicated in future studies.

1.2 The SLATINT Project

1.2.1 Participant Countries

In April 2007, a group of researchers and professors from five Latin American countries (Brazil, Chile, Colombia, Mexico, and Peru), had a meeting in the city of Belo Horizonte, Brazil. This meeting took place during the VIII Meeting of Psychological Assessment of Minas Gerais State. In this meeting, we analyzed the possibility of conducting a large-scale assessment of intelligence with samples of each Latin American country. In subsequent face-to-face meetings and videoconferences, the design of the project was discussed (e.g., number and kind of tests, age, sample size, data collection calendar, standardized procedure for the testing sessions, etc.). Shortly thereafter, a colleague from Cuba and another from Mozambique were contacted and invited to participate. However, due to political reasons for the first and economic factors for the latter, these two countries could not participate. In 2008, a colleague from Argentina joined our emerging project. Additionally, for comparison purposes, we sought out a sample of students from a developed country. Considering the cultural proximity, the obvious choice was Spain. Professor Roberto Colom of the Universidad Autónoma de Madrid assisted us by contacting a Spanish colleague for the data collection in Madrid. Finally, we named the project "The Study of the Latin American Intelligence" (SLATINT).

1.2.2 Design Adjustments

The project was designed to be simple (budget constraints) and practical (minimal interruption of normal school activities). Nevertheless, there was several limitations. Firstly, the defined age group for this project was 14–15 years instead of 16 years, the average age in which intelligence reaches its peak of development (Lynn, 1999). According to our Mexican colleague, it would be difficult to find 16-year-old students enrolled in Mexican public schools. Effectively, according to the OECD, Mexico has one of the lowest enrollment rates for 15-year-old students of all Latin America countries (https://www.oecd.org/edu/Mexico-EAG2014-Country-Note-spanish.pdf).

The second problem related to the official entrance age for primary education. All students had initiated their schooling at 6 years of age, except Brazilian students who began at 7 years of age (currently, Brazilian students start at 6 years of age). Thus, at 14 and 15 years of age, Brazilian students in our study had 8 and 9 years of schooling, respectively, while samples from others countries had between 9 and 10 years of schooling. We consider that the difference in years of schooling among Brazilian students and other students was not a solvable problem. Thus, we decided to test schoolrooms where students aged 14 and 15 years were concentrated.

The third problem was related to cognitive measures. The tasks needed to be short and varied. Our Chilean colleague suggested a group of 25 subtests of the German cognitive battery, the Berlin Intelligence Structure Model or BIS, administered by him to Chilean students years ago, with reasonable results (Rosas, 1992, 1996). Each task took between 1 and 2 minutes to complete. Considering the two longest and imperative measures for this study (Raven's Standard Progressive Matrices and the PISA test), we chose to only use nine non-verbal tasks. Regarding the PISA test, we applied a short 2003 version (emphasis on mathematics), which was available on the website of the Brazilian Ministry of Education. This version contained 29 items. A pilot study with 181 Brazilian students indicated an alpha coefficient of 0.906 and the test took, on average, 2 hours. In order to shorten the time of general testing, we decided to use a shorter version of PISA. The rash model indicated the possibility of deleting a maximum of 13 items. The reliability of the new version (16 items) was 0.875. Again, we conducted a second pilot study with PISA: 16 items in a sample of 167 Brazilian students. The new version took, on average, 1 hour and 15 minutes. The reliability was 0.844, and it was associated with the Raven test at 0.650. Thus, the short version of PISA preserved its reliability and validity. Native Portuguese and Spanish speakers conducted double-check translation of the PISA test (Portuguese to Spanish language).

The fourth problem was related to access to schools, especially difficult in Mexico and Spain. For this reason, we decided that the administration of the complete battery of cognitive measures would only be to a small Mexican sample, and the PISA and the SPM test would be administered to a large sample. In the case of Spain, all cognitive measures were administered to a small sample.

The fifth challenge was related to the socioeconomic status (SES) of students. There is no regional socioeconomic measure available for all Latin American countries. Therefore, the most direct approach to identify students with a low, middle, and high SES would be to have student participation from private and public schools. In general, Latin American public schools have a higher concentration of students with a low SES, and private schools tend to have more students with a middle and high SES. However, our Peruvian colleagues informed us of the existence of a reasonable number of poor private schools in the city of Lima that receive students with a low SES. Moreover, in Chile, the government provided an extensive system of education vouchers to private schools. Thus, there were students with a high, middlem or low SES in private schools. Definitively, therefore, the type of school (private or public) was not a reliable criterion to attain access to students with a middle or high SES. On the other hand, Spain had less socioeconomic inequality. The type of school (private or public) did not segregate students in Spain in the same way as Latin American countries did. Therefore, we decided that at least two schools from each SES level (low, middle, and high) would be invited to participate in this project, independent of the type of school (i.e., private or public). This selection would be done according to the knowledge of researchers of their cities. In order to investigate the validity of the school SES classifications, researchers completed a questionnaire about each school selected. The questionnaire was administered 1 year after completing the data collection, and it focused on sanitation and urban conditions (e.g., waste-collection system, drainage system, public street lighting, and presence of paved roads) and items regarding school environment (e.g., school instruction time, class size, mathematics instruction time, presence of computers). The points accumulated by each item were summed, producing a total score. The average correlation between the information of this questionnaire and school-SES (socioeconomic classification done by researchers) was 0.679 (except for Argentina and Spain, who did not collect information), indicating a large effect correlation (or good validity).

Additionally, in order to obtain direct information regarding student SES, we created a questionnaire with items based on two sources: available resources (expected in 2008) within their home (e.g., cable TV, MP3 player, phone, computer, internet, videogames, weekend magazine) and parents' level of education. The first source represents points accumulated by each item, yielding a total score. For the second source, the lowest educational level was represented by 1 (incomplete primary), and the highest educational level was represented by 6 (university graduate). The new variable was termed "individual-SES." As Argentina and Spain did not administer the questionnaire regarding their schools, we estimated the correlation between individual SES and school SES classification. Correlations of 0.622 for Argentina and 0.117 (non-statistically significant) for Spain were obtained when parents' education was disregarded for the individual SES. This result demonstrated that the socioeconomic classification of Argentine schools strongly followed the SES of their students, and, as expected, this tendency was not observed in the case of Spanish schools due to lesser socioeconomic inequality in Spain. For the remainder of Latin American samples, Chile and Colombia demonstrated the lowest correlations (0.490 and 0.518, respectively) between individual SES and school SES. Taken together, we considered the socioeconomic classification elaborated for the schools that participated in the present project as valid.

1.2.3 Final Design of the SLATINT Project

In each country, two schools (at least) representative of each socioeconomic stratum (low, middle, and high SES) were selected. Considering time limits for testing in schools, we decided that the most important tests, the PISA test and the SPM test, would be applied to the whole sample from each country. Other cognitive measures (e.g., the BIS subtests) would be applied to a subsample. The final set of questionnaires, cognitive measures, time of administration, and distribution are presented on Table 1.1.

All the tests were collectively administered inside the classroom and divided into two or three sessions according to school availability. In total, 11 cognitive measures (the PISA test included) and a socioeconomic questionnaire were administered.

Table 1.1 Questionnaires and cognitive measures administered in the SLATINT Project

Measure	Description	Time	Sample assessed
SES questionnaire	Socioeconomic questionnaire	5'	Whole
PISA test-16 items	School achievement test	75'	Whole
SPM	Figural reasoning test	45'	Whole
BIS_PF	Figural reasoning test	1'40"	Partial
BIS_MF	Figural short term memory test	1' to memorize and 1' to execute	Partial
BIS_PN2	Numerical simple mental speed test	1'20"	Partial
BIS_RF	Figural simple mental speed test	1'	Partial
BIS_PN3	Numerical reasoning test	1'40"	Partial
BIS_RN3	Numerical reasoning test	1'15"	Partial
BIS_RN1	Numerical simple mental speed test	1'15"	Partial
BIS_CF2	Figural creativity test	1'20"	Partial
BIS_CV1	Verbal creativity test	1'15"	Partial

Note: The SES questionnaire included items regarding available resources in home, age, sex, hometown, birth order, native language, number of dependents, early childhood environment, parents' education, and job occupation of the main family provider. *SPM* Raven's Standard Progressive Matrices, *BIS* Berlin Intelligence Structure Model. Time in minutes (') and seconds (")

1.2.4 Financing and Logistics

The Brazilian test publisher company VETOR, through its CEO Mr. Glauco Bardella, sponsored the logistics of the SLATINT Project. Between 2008 and 2009, psychological tests were purchased and sent to each participating country. Additionally, VETOR paid psychologists and research assistants for data collection in each country (except for Brazil, where psychology professors and their volunteer students conducted the data collection). At the end of 2009, the project received a grant (n° 490312/2008-0) from the Brazilian National Council for Scientific and Technological Development (CNPq, Portuguese acronym), providing financial support for costs associated with shipping and receiving material between Belo Horizonte and the other Latin-American cities.

Following the data collection stage, all material from each country was sent to the *Laboratorio de Avaliação das Diferenças Individuais* (Laboratory of Individual Differences Assessment), Department of Psychology at the Federal University of Minas Gerais, Brazil. Codification (id-country and id-subject) for each test/measure, estimation of raw scores and data computation were performed onsite by a team of students (undergraduate research mentorship) specially trained by the laboratory. To guarantee the absence of typing errors, independent examiners triple-checked all work.

1.2.5 Final Sample

The complete dataset comprised 4,282 students enrolled in 66 schools. However, there were 332 students (or 8% of the total sample) of 13 and 16 years of age (distortion age/school grade). Data from these students were not considered in the statistical analysis. Table 1.2 indicates the number of respondents to each measure (socioeconomic and cognitive), and listwise (number of respondents after deletion of missing data for some measure).

In general, our Latin American sample was characterized by a slight female predominance (50.7%); 94% living in an urban context; 53.9% enrolled in private schools; 80% attending ninth and tenth grade; 70% enrolled in schools of middle (37%) and high (33%) SES; 44% from families with the father as the main provider; 66% of households composed of, at least, four members; 45% first-born; and 1% were immigrant students (however, the Spanish sample had 24% of immigrants). Readers must note that this general description varied according to the sampled country for each measure. In this sense, some variation in the socioeconomic profile was expected according to the sample used for the statistical analysis in the upcoming chapters.

1.3 Organization of this Book

This book presents seven chapters related to intelligence and school performance. In each chapter, the SLATINT Project results are presented. The readers can read from the start of the book to the end, or read specific chapters, according to their interest.

Table 1.2 Number of assessments for each measure and each national sample

Measure	Argentina	Brazil	Chile	Colombia	Mexico	Peru	Spain	Total
SES quest	532 (497)	652 (636)	548 (532)	634 (603)	646 (591)	556 (528)	139 (127)	3707 (3514)
PISA	575	626	574	677	671	577	145	3845
SPM	578	735	573	676	671	572	145	3950
BIS_PF	448	189	169	207	53	327	146	1539
BIS_MF	448	189	169	207	53	327	146	1539
BIS_PN2	448	189	169	208	53	327	146	1540
BIS_RF	448	189	169	208	53	326	146	1539
BIS_PN3	448	189	169	208	53	327	146	1539
BIS_RN3	448	189	169	208	53	326	146	1539
BIS_RN1	448	189	169	208	53	326	146	1539
CF2	448	189	169	208	53	326	146	1539
CV1	448	189	169	208	53	326	146	1539
Listwise1	1311							
Listwise2	1455							
Listwise3	3787							

Note: *SES quest* socioeconomic questionnaire (between parenthesis data of individual-SES + Parents' education), *Listwise 1* number of respondents who answered all measures after deletion of missing values in some measure, *Listwise 2* number of respondents to all cognitive measures, *Listwise 3* number of respondents to the PISA and the SPM test

Chapter 2 is dedicated to verifying the factorial structure of administered cognitive measures. Our goal was to identify the existence of intelligence as a general factor (or *g* factor), and Chapter 3 presents the effect of education and social variables on this *g* factor.

Chapter 4 goes beyond test scores, verifying how the minds of good and poor problem-solvers work, using cognitive and processing-information models. Addressing the cognitive psychology as complementary knowledge to the psychometric science would be an improvement in understanding the cognitive performance exhibited by human groups. Additionally, Chapter 4 is dedicated to creativity, which is recognized as an important factor in dealing with the demands of our modern world. Creativity is usually linked to the ability to create new solutions and solve the hardest problems. Supposedly, a creative advantage can benefit people, as well as nations, in achieving their goals and development.

Chapter 5 is dedicated to a sensitive but important subject for understanding the human capital available in a nation. This subject is cognitive sex differences. Studies from developing countries are rare. The SLATINT Project presents their results from an unbiased perspective.

Chapter 6 analyzes the human capital available in the region in terms of IQ and compares the results obtained from Latin American samples with the performance of Spanish students.

Chapter 7 summarizes the results obtained by the SLATINT Project and analyzes the challenges and future prospects for the region.

References

Astorga, P., Bergés, A. R., & Fitzgerald, V. (2004). *The Oxford Latin American economic history database (OxLad)*. Oxford: The Latin American Centre at Oxford University Online.

Barber, N. (2005). Educational and ecological correlates of IQ: A cross-national investigation. *Intelligence, 33*, 273–284.

Beier, M. E., & Ackerman, P. L. (2001). Current events knowledge in adults: an investigation of age, intelligence and non-ability determinants. *Psychology and Aging, 16*(4), 615–628.

Beier, M. E., & Ackerman, P. L. (2003). Determinants of health knowledge: an investigation of age, gender, abilities, personality, and interests. *Journal of Personality and Social Psychology, 84*(2), 439–448.

Beier, M. E., & Ackerman, P. L. (2005). Age, ability, and the role of prior knowledge on the acquisition of new domain knowledge: promising results in a real-world learning environment. *Psychology and Aging, 20*(2), 341–355.

Cunningham, W., Acosta, P., & Muller, N. (2016). *Minds behavior at work: boosting emotional skills for Latin America's Workforce*. Washington, DC: World Bank Group.

Dickerson, R. E. (2006). Exponential correlation of IQ and the wealth of nations. *Intelligence, 34*, 292–295.

Donghi, T. H. (2005). *História conteporânea de América Latina*. Madrid: Alianza.

Economic Commission for Latin America and the Caribbean. (2017). *Social Panorama of Latin America, 2016 (LC/PUB.2017/12-P)*. ECLAC/UM: Santiago.

Farret, R. L., & Pinto, S. R. (2011). América Latina: da construção do nome à consolidação da ideia. *Topoi (Rio de Janeiro), 12*(23), 30–42.

Gelade, G. A. (2008). IQ, cultural values, and the technological achievement of nations. *Intelligence, 36*, 711–718.

Geoff, D., Batty, G. D., & Deary, I. J. (2009). The association between IQ in adolescence and a range of health outcomes at 40 in the 1979 US National Longitudinal Study of Youth. *Intelligence, 37*, 573–580. https://doi.org/10.1016/j.intell.2008.12.002

Gottfredson, L. S. (1997). Mainstream science on intelligence: An editorial with 52 signatories, history, and bibliography. *Intelligence, 24*(1), 13–23.

Gottfredson, L. S. (1999). The nature and nurture of vocational interests. In M. L. Savickas & A. R. Spokane (Eds.), *Vocational interests: Their meaning, measurement, and use in counseling* (pp. 57–85). Palo Alto: Davies-Black.

Gottfredson, L. S. (2002). Where and why g matters: Not a mystery. *Human Performance, 15*, 25–46.

Gottfredson, L. S. (2003). Jobs and life. In H. Nyborg (Ed.), *The scientific study of general intelligence* (pp. 293–342). Amsterdam: Pergamon.

Gottfredson, L. S. (2006). Consequências sociais das diferenças de grupo em habilidade cognitiva. In C. E. Flores-Mendoza & R. Colom (Eds.), *Introdução à psicologia das diferenças individuais* (pp. 433–456). Porto Alegre: Artmed.

Hirschi, T., & Hindelang, M. J. (1997). Intelligence and delinquency: a revisionist review. *American Sociological Review, 42*(4), 571–587.

Hunt, E. B. (2010). *Human Intelligence*. New York: Cambridge University Press.

Jones, G., & Schneider, W. J. (2006). Intelligence, human capital, and economic growth: A bayesian averaging of classical estimates (BACE) approach. *Journal of Economic Growth, 11*, 71–93.

Jones, G., & Schneider, W. J. (2010). IQ in the production function. *Economic Inquiry, 48*, 743–755.

Kanazawa, S. (2006). IQ and the wealth of states. *Intelligence, 34*, 593–600.

Kuncel, N. R., Hezlett, S. A., & Ones, D. S. (2004). Academic performance, career potential, creativity, and job performance: Can one construct predict them all? *Journal of Personality and Social Psychology, 86*(1), 148–161.

Lynam, D., Moffitt, T., & Stouthamer-Loeber, M. (1993). Explaining the relation between IQ and delinquency: class, race, test motivation, school failure, or self-control? *Journal of Abnormal Psychology, 102*(2), 187–196.

Lynn, R. (1999). Sex differences in intelligence and brain size: A developmental theory. *Intelligence, 27*(1), 1–12.

Lynn, R., & Mikk, J. (2007). National differences in intelligence and educational attainment. *Intelligence, 35*, 115–121.

Lynn, R., & Vanhanen, T. (2002). *IQ and the wealth of nations*. Westport, CT: Praeger.

Lynn, R., & Vanhanen, T. (2006). *IQ and global inequality*. Washington: Summit.

Lynn, R., & Vanhanen, T. (2012). *Intelligence: A unifying construct for the social sciences*. Londres: Ulster Institute for Social Research.

Lynn, R., Harvey, J., & Nyborg, H. (2009). Average intelligence predicts atheism rates across 137 nations. *Intelligence, 37*, 11–15.

Lynn, R., Meisenberg, G., Mikk, J., & Williams, A. (2007). National IQs predict differences in scholastic achievement in 67 countries. *Journal of Biosocial Science, 39*, 861–874.

Lynn, R., & Meisenberg, G. (2010). National IQs calculated and validated for 108 nations. *Intelligence, 38*, 353–360. https://doi.org/10.1016/j.intell.2010.04.007

Meisenberg, G. (2008). How does racial diversity raise income inequality. *The Journal of Social Political, and Economic Studies, 33*, 3–26.

Neisser, U., Boodoo, G., Bouchard, T., Boykin, A., Brody, N., Ceci, S., … Urbina, S. (1996). Intelligence: Knowns and unknowns. *American Psychologist, 51* (2), 77–101.

OECD. (2003). *First results from PISA 2003. Executive summary, OECD learning for tomorrow's world first results from PISA 2003*. Paris: OECD.

OECD. (2007). *PISA 2006. Science competencies for tomorrow's world. Vol. 1–Analysis*. Paris: OECD.

OECD. (2010). *PISA 2009 Results: Learning trends. Changes in student performance since 2000* (Vol. V). https://doi.org/10.1787/9789264091580-en.

OECD. (2013). PISA 2012 Results in Focus. In *What 15-years-olds know and what they can do with what they know*. Paris: OECD.

OECD/ECLAC/CAF. (2016). *Latin American Economic Outlook 2017: Youth, skills and entrepreneurship*. Paris: OECD. https://doi.org/10.1787/leo-2017-en

PNUD. (2010). *Informe regional sobre desarrollo humano para América Latina y el Caribe 2010. Actuar sobre el futuro: Romper la transmission inter-geracional de la desigualdad*. San Jose de Costa Rica: Editorama SA.

Reeve, C. L. (2009). Expanding the g-nexus: Further evidence regarding the relations among national IQ, religiosity and national health outcome. *Intelligence, 37*, 495–505.

Revelle, W., Wilt, J., & Condon, D. (2011). Individual differences and differential psychology: A brief history and prospect (Chap. 1). In T. Chamorro-Premuzic, A. Furnham, & S. Von Stumm (Eds.), *Handbook of individual differences* (pp. 3–38). Oxford: Wiley-Blackwell.

Rindermann, H. (2007). The g-factor of international cognitive ability comparisons: The homogeneity of results in PISA, TIMSS, PIRLS and IQ-tests across nations. *European Journal of Personality, 21*, 667–706.

Rindermann, H., & Meisenberg, G. (2009). Relevance of education and intelligence at the national level for health: The case of HIV and AIDS. *Intelligence, 37*, 383–395.

Rosas, R. (1992). Existo Academico Universitario: Problemas de su Definición, Medición y Predicción. *PSYKHE, 1*, 25–39.

Rosas, R. (1996). Replicación del Modelo de Estructura de Inteligencia de Berlín en una Muestra de Estudiantes Chilenos. *PSYKHE, 5*, 39–56.

Rushton, J. P., & Templer, D. I. (2009). National differences in intelligence, crime, income, and skin color. *Intelligence, 37*, 341–346.

Shatz, S.M. (2008). IQ and fertility: A cross-national study. *Intelligence, 36*, 109–111. https://doi.org/10.1016/j.intell.2007.03.002.

Sternberg, R. J., & Detterman, D. K. (1986). *What is intelligence? Contemporary viewpoints on its nature and definition*. Norwood: Ablex.

Thurstone, L. L. (1921). Contribution to intelligence and its measurement: A symposium. *Journal of Educational Psychology, 12*, 201–207.

Walker, N. P., McConville, P. M., Hunter, D., Deary, I. J., & Whalley, L. J. (2002). Childhood mental ability and lifetime psychiatric contact: A 66-year follow-up study of the 1932 Scottish Mental Ability Survey. *Intelligence, 30*(3), 233–245.

Whetzel, D. L., & McDaniel, M. A. (2006). Prediction of national wealth. *Intelligence, 4*, 449–458.

World Economic Forum - WEF (2016). *The future of Jobs. Employment, skills, and workforce strategy for the fourth industrial revolution*. Retrieved from http://www3.weforum.org/docs/WEF_FOJ_Executive_Summary_Jobs.pdf.

Chapter 2
Cognitive Factor Structure: The *g* Factor

Abstract One century of intelligence research, generally performed on samples from developed countries, has shown the existence of a general model of intelligence (or *g* factor). In our study, we tested this model using data from the SLATINT Project. A positive manifold of correlations was found and results from SEM modeling (Structural Equation Modeling), using the total sample and each Latin American sample, indicated that a single-factor model (or *g* factor) fit the data adequately, i.e., a general cognitive ability influenced performance on a set of cognitive ability measures.

2.1 The *g* Factor

Charles Edward Spearman (1863–1945), the first researcher to statistically study intelligence, analyzed mental abilities under the variability of cognitive performance. Spearman challenged the prevailing belief that poor performance of a person in one type of mental activity could be compensated for with superior performance in another. Through the observation of positive inter-test correlations, Spearman developed the technique called *Factorial Analysis*, from which he extracted a factor that is common to all cognitive measures (termed the *g* factor) and a specific factor (the S factor) that is uncorrelated to the common factor or with any other of the specific factors. This understanding of intelligence permitted Spearman to propose his *Two Factors Theory of Intelligence* (Spearman, 1927). Several criticisms regarding the uniqueness ("*The individual has as many g's as you administer tests*"), transformation ("*g is merely relative to the set up*"), and indeterminateness ("*g is in part indeterminate*") were contested by Spearman when he presented a table of positive, and almost identical, correlations between different methods of factorizing and factor loadings. For Spearman, *g* was unique, and the same, independent of the applied cognitive tests (indicator of the indifference principle). The indeterminateness was a "defect of exactness," an ordinary error that does not affect the existence of the object measured (Spearman & Jones, 1950). However, Spearman refused to respond to what *g* is. He preferred to assert that his methods of analysis permit where *g* can be found, but not what it is like (Spearman, 1927).

C. Flores-Mendoza et al., *Intelligence Measurement and School Performance in Latin America*, https://doi.org/10.1007/978-3-319-89975-6_2

Since Spearman's work, the American psychologist Arthur Jensen has arguably been the main defender of the *g* factor (Jensen, 1998). Jensen considered the term "*g* factor" as an evolutionary biological variable, perhaps the most important psychological construct in behavioral science. According to Jensen, the *g* factor helps to make diffuse terms such as intelligence or mental ability more objective and precise.

In this sense, Jensen asserted that a general and powerful factor, or *g*, would emerge from a large battery of cognitive tests. This general factor could be extracted from whatever the applied factor analysis. An exception would be the orthogonal methods, which presume independence of factors. A better method of representing *g* would be through the hierarchical model, where psychological tests are at the first level, primary factors at the second level, secondary factors at the third level, and the general factor at the final level (Fig. 2.1).

Based on several studies that used IQ tests, which to some extent represent *g*, Jensen showed biological correlations (e.g., head size, brain size, stature, patterns of evoked brain potentials) and practical validity (e.g., scholastic performance, job training, job performance, welfare status) of the *g* factor, which would demonstrate its existence beyond factor analysis. Therefore, the *g* factor would be a biological phenomenon, not a statistical artefact. This is a position strongly defended by the American sociologist Linda Gottfredson, who wrote the famous statement about the mainstream of intelligence, with the approval of 52 experts, among them Arthur Jensen (Gottfredson, 1997).

One of the most recent and sophisticated studies regarding the factorial structure of intelligence belongs to the American psychometrician John Carroll, who analyzed 450 datasets used in previous investigations (Carroll, 1993). This work concluded that the structure of human intelligence could be represented in three strata: narrow (I), broad (II), and general (III). According to Carroll, the last stratum (of the Three-Stratum model) " … is highly similar to the Spearman-Holzinger model. Stratum III is essentially the same as what Spearman called g … " (p. 637).

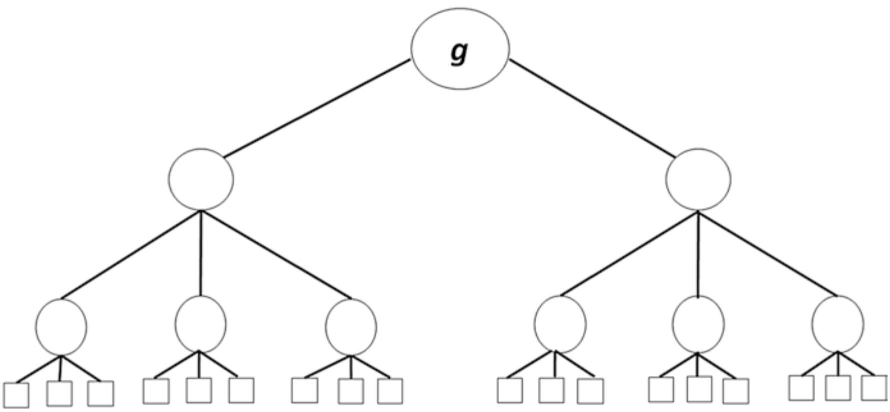


Fig. 2.1 Hierarchical model of intelligence: The *g* factor

Considering the increasing development of psychological measurement, some studies (Jensen & Weng, 1994; Ree & Earles, 1991; Thorndike, 1987) verified the stability of *g* through different methods of factor extraction, as was performed by Spearman in the early twentieth century. The new studies showed the possibility of extracting a general factor regardless of the method used, and responded to the challenge of proving the uniqueness of *g*.

In order to test if the *g* factor extracted from a battery of cognitive tests is the same *g* extracted from another battery, Johnson, Bouchard, Krueger, McGue, and Gottesman (2004) analyzed three different cognitive batteries administered to the same sample of adults ($N = 436$). The three *g* factors correlated between .99 and 1.00, indicating that Johnson et al. identified a common underlying factor of general intelligence. These results received criticism regarding the transformation of *g* according to the battery used.

Throughout the twentieth century, up to the present-day, the controversy regarding the existence of the *g* factor has remained active, although currently with less intensity.

For example, Howard Gardner, the American psychologist who proposed the *Multiple Intelligence Model* (Gardner, 1983), has been the most popular critic of the *g* factor. Despite the lack of scientific evidence (Jensen, 2008), Gardner's theory continues to have a strong influence on the current educational system. Another theory, this time based on empirical evidence, and called the *Triarchic Theory of Intelligence*, is the proposal by Robert Sternberg (Sternberg, 1985). Sternberg does not deny strong evidence in favor of a general factor of intelligence, he simply identifies other components of intelligence that can create a practical profile of individual differences that are different from that of academic intelligence. This profile would be highly correlated to the success of people. According to Sternberg, "g would not be the only house" (Sternberg, 2003, p. 373).

Another attempt to challenge the *g* factor assumption was made by Floyd, Shands, Rafael, Bergeron, and McGrew (2009). Beyond verifying the effects of different methods of extracting factors, these authors verified the effect of the number of tests in the battery on the general factor. Their results indicated that the kind of method used for extraction of factors, the test battery composition, and the battery size affected general factor loadings.

We were not able to find any study of the *g* factor using Latin American samples. Thus, the first aim in the SLATINT Project was to verify the presence of the *g* factor across a battery of cognitive measures.

2.2 The *g* Factor in Latin American Samples

Table 2.1 shows descriptive statistics of each cognitive/school measure and reliability for each sample (including the Spanish sample). Results show that three cognitive measures (BIS_PF, BIS_RN1, and BIS_PN2) had the lowest reliability indices of all samples. In addition, the smallest sample that completed all cognitive battery testing was from Mexico. Thus, the results should be interpreted with caution.

Table 2.1 Descriptive statistics for each sample and cognitive measure

Countries	Measures	*N*	Min.	Max.	Mean	SD	*α*
Argentina	SPM	578	7	60	43.7	8.6	.902
	PISA	575	0	15	6.8	3.8	.811
	BIS_PF	448	0	7	3.3	1.7	.600
	BIS_MF	448	0	20	11.1	4.8	.844
	BIS_RF	448	7	25	17.8	4.0	.874
	BIS_PN3	448	0	9	3.3	1.9	.869
	BIS_RN3	448	0	38	14.7	5.8	.720
	BIS_RN1	448	0	10	3.1	2.4	.607
	BIS_PN2	448	0	8	3.6	1.5	.601
Brazil	SPM	735	9	60	42.6	8.7	893
	PISA	626	0	16	6.2	3.9	.803
	BIS_PF	189	0	7	2.8	1.6	.600
	BIS_MF	189	2	20	11.9	4.9	.847
	BIS_RF	189	7	25	18.8	4.7	.913
	BIS_PN3	189	0	9	3.2	1.9	.874
	BIS_RN3	189	1	39	15.9	5.8	.796
	BIS_RN1	189	0	13	3.7	2.9	.644
	BIS_PN2	189	0	10	3.5	1.6	.600
Chile	SPM	573	8	59	45.4	7.5	.893
	PISA	574	0	16	6.6	3.9	.838
	BIS_PF	169	0	7	3.5	1.6	.600
	BIS_MF	169	2	20	12.3	4.5	.827
	BIS_RF	169	7	25	17.7	4.5	.905
	BIS_PN3	169	0	9	3.3	1.8	.834
	BIS_RN3	169	4	26	14.1	4.7	.701
	BIS_RN1	169	0	12	3.9	2.5	.601
	BIS_PN2	169	0	7	3.6	1.5	.600
Colombia	SPM	676	11	59	43.0	6.9	.829
	PISA	677	0	15	5.7	3.0	.700
	BIS_PF	207	0	7	3.1	1.6	.599
	BIS_MF	207	0	20	12.9	4.9	.867
	BIS_RF	208	7	25	18.7	5.1	.907
	BIS_PN3	208	0	9	3.0	1.9	.910
	BIS_RN3	208	5	46	15.6	6.7	.841
	BIS_RN1	208	0	14	3.5	3.3	.642
	BIS_PN2	208	0	8	3.7	1.5	.598
Mexico	SPM	671	7	59	46.8	6.5	.790
	PISA	671	0	16	7.4	3.6	.865
	BIS_PF	53	0	7	4.8	1.5	.599
	BIS_MF	53	11	20	17.3	3.3	.830
	BIS_RF	53	20	25	24.5	.9	.600
	BIS_PN3	53	1	9	5.3	1.5	.600
	BIS_RN3	53	7	36	19.3	4.9	.857
	BIS_RN1	53	1	14	7.6	2.3	.600
	BIS_PN2	53	1	7	4.3	1.4	.600

(continued)

Table 2.1 (continued)

Countries	Measures	*N*	Min.	Max.	Mean	SD	α
Peru	SPM	572	6	60	48.4	7,3	.880
	PISA	577	0	16	7.1	3,9	.815
	BIS_PF	327	0	7	3.6	1,7	.600
	BIS_MF	327	1	20	15.2	4,4	.861
	BIS_RF	326	9	25	21.5	3,5	.871
	BIS_PN3	327	0	9	4.4	1,8	.911
	BIS_RN3	326	5	48	21.0	7,1	.832
	BIS_RN1	326	0	16	5.6	3,6	.600
	BIS_PN2	327	0	9	4.6	1,6	.600
Spain	SPM	145	26	58	48.7	6,1	.859
	PISA	145	0	15	7.6	3,8	.800
	BIS_PF	146	0	7	3.9	1,6	.600
	BIS_MF	146	0	20	13.4	4,3	.817
	BIS_RF	146	9	25	19.3	4,1	.877
	BIS_PN3	146	0	9	3.9	2,1	.915
	BIS_RN3	146	2	47	18.6	6,6	.787
	BIS_RN1	146	0	15	4.5	2,9	.700
	BIS_PN2	146	0	9	4.4	1,7	.600
Latin America	SPM	3805	6	60	44.9	7.9	.897
	PISA	3700	0	16	6.6	3.8	.811
	BIS_PF	1393	0	7	3.4	1.7	.600
	BIS_MF	1393	0	20	12.8	4.9	.864
	BIS_RF	1393	7	25	19.2	4.6	.898
	BIS_PN3	1394	0	9	3.6	1.9	.904
	BIS_RN3	1393	0	48	16.6	6.6	.812
	BIS_RN1	1393	0	16	4.1	3.2	.630
	BIS_PN2	1394	0	10	3.9	1.6	.602

Note: *SPM* Standard Progressive Matrices of Raven, *PISA* PISA test, *BIS_PF* Figural reasoning test, *BIS_MF* Memory Figural Test, *BIS_RF* Figural simple mental speed test, *BIS_PN3* Numerical reasoning test, *BIS_RN3* Numerical reasoning test, *BIS_RN1* Numerical simple mental speed test, *BIS_BIS_PN2* Numerical simple mental speed test. *SD* Standard deviation

2.2.1 Correlation Matrices

Through correlation matrices, it is possible to observe a positive association among all cognitive measures for all samples, except for the Mexican sample where only a few significant associations were observed. One explanation for the relative independence between cognitive measures in the Mexican sample could be linked to the type of sample. For the PISA and the SPM test, the recruited Mexican sample ($N = 671$) came from low, medium, and high SES schools. However, for the BIS subtests, the sample ($N = 53$) came exclusively from a high SES school. Thus, large socioeconomic (and cognitive) variability strengthened correlations between PISA and SPM, while small socioeconomic variability (and small cognitive variability) weakened correlations among the BIS tests. In differential psychology, this phenomenon is known as Spearman's *Law of Diminishing Returns*, where *g* saturation (or positive manifold of correlations) might be stronger at the low end of the ability distribution. In other words, the *g* saturation decreases as ability level increases (Detterman & Daniel, 1989). The Mexican sample that took the BIS tests came from a high SES school and can be considered a high ability group (see the mean score of the PISA and SPM test). Thus, the lower than average correlation between cognitive measures was theoretically expected for this group.

Considering the total Latin American sample, the matrix of correlations showed a positive association among all measures (Tabs. 2.2–2.9). These results indicated the existence of a latent general factor, i.e., the *g* factor or general cognitive ability.

2.2.2 Determining the Factor Structure of g

SEM modeling (a multivariate statistical analysis technique used to analyze structural relationships) was conducted using the EQS 6.1 software (Bentler, 1985). Our first step was to identify the factor structure of general intelligence using data from

Table 2.2 Correlation matrix for the Argentina sample

	SPM	PISA	BIS_PN3	BIS_RN3	BIS_RN1	BIS_MF	BIS_RF	BIS_PF	BIS_PN2
SPM	1	.584**	.436**	.245**	.351**	.356**	.213**	.288**	.294**
PISA		1	.524**	.394**	.453**	.380**	.185**	.279**	.327**
BIS_PN3			1	.369**	.397**	.280**	.181**	.258**	.294**
BIS_RN3				1	.405**	.207**	.228**	.165**	.318**
BIS_RN1					1	.307**	.108*	.276**	.338**
BIS_MF						1	.285**	.286**	.251**
BIS_RF							1	.212**	.130**
BIS_PF								1	.199**
BIS_PN2									1

*Correlation significant at the .05 level
**Correlation significant at the .01 level

Table 2.3 Correlation matrix for the Brazilian sample

	SPM	PISA	BIS_PN3	BIS_RN3	BIS_RN1	BIS_MF	BIS_RF	BIS_PF	BIS_PN2
SPM	1	.599**	.488**	.337**	.548**	.420**	.243**	.125	.295**
PISA		1	.466**	.416**	.586**	.295**	.207**	.156	.334**
BIS_PN3			1	.503**	.527**	.343**	.283**	.237**	.428**
BIS_RN3				1	.602**	.238**	.327**	.136	.410**
BIS_RN1					1	.340**	.204**	.224**	.392**
BIS_MF						1	.150*	.125	.206**
BIS_RF							1	.253**	.266**
BIS_PF								1	.139
BIS_PN2									1

*Correlation significant at the .05 level
**Correlation significant at the .01 level

Table 2.4 Correlation matrix for the Chilean sample

	SPM	PISA	BIS_PN3	BIS_RN3	BIS_RN1	BIS_MF	BIS_RF	BIS_PF	BIS_PN2
SPM	1	.649**	.492**	.357**	.435**	.440**	.344**	.280**	.412**
PISA		1	.598**	.423**	.538**	.500**	.279**	.323**	.498**
BIS_PN3			1	.328**	.346**	.414**	.266**	.309**	.264**
BIS_RN3				1	.381**	.236**	.302**	.173*	.394**
BIS_RN1					1	.339**	.289**	.294**	.360**
BIS_MF						1	.188*	.358**	.156*
BIS_RF							1	.298**	.149
BIS_PF								1	.221**
BIS_PN2									1

*Correlation significant at the .05 level
**Correlation significant at the .01 level

Table 2.5 Correlation matrix for the Colombian sample

	SPM	PISA	BIS_PN3	BIS_RN3	BIS_RN1	BIS_MF	BIS_RF	BIS_PF	BIS_PN2
SPM	1	.468**	.306**	.222**	.205**	.172*	.108	.100	.350**
PISA		1	.300**	.189**	.371**	.164*	-.013	.155*	.218**
BIS_PN3			1	.432**	.410**	.200**	.211**	.303**	.405**
BIS_RN3				1	.309**	.242**	.366**	.207**	.424**
BIS_RN1					1	.177*	.203**	.212**	.292**
BIS_MF						1	.158*	.179**	.218**
BIS_RF							1	.195**	.183**
BIS_PF								1	.308**
BIS_PN2									1

*Correlation significant at the .05 level
**Correlation significant at the .01 level

Table 2.6 Correlation matrix for the Mexican sample

	SPM	PISA	BIS_PN3	BIS_RN3	BIS_RN1	BIS_MF	BIS_RF	BIS_PF	BIS_PN2
SPM	1	.633**	.276*	.132	.106	.116	−.006	.188	.173
PISA		1	.318*	.155	.123	.250	−.006	.241	.350*
BIS_PN3			1	.454**	.339*	.079	−.147	.147	.403**
BIS_RN3				1	.595**	−.027	.047	−.072	.222
BIS_RN1					1	.170	−.117	.050	.006
BIS_MF						1	−.026	.302*	−.055
BIS_RF							1	−.080	−.010
BIS_PF								1	.185
BIS_PN2									1

*Correlation significant at the .05 level
**Correlation significant at the .01 level

Table 2.7 Correlation matrix for the Peruvian sample

	SPM	PISA	BIS_PN3	BIS_RN3	BIS_RN1	BIS_MF	BIS_RF	BIS_PF	BIS_PN2
SPM	1	.548**	.408**	.307**	.363**	.264**	.175**	.240**	.230**
PISA		1	.498**	.458**	.513**	.240**	.064	.212**	.369**
BIS_PN3			1	.381**	.396**	.162**	.148**	.275**	.336**
BIS_RN3				1	.456**	.192**	.155**	.071	.327**
BIS_RN1					1	.172**	.087	.142*	.297**
BIS_MF						1	.302**	.174**	.241**
BIS_RF							1	.080	.132*
BIS_PF								1	.120*
BIS_PN2									1

*Correlation significant at the .05 level
**Correlation significant at the .01 level

Table 2.8 Correlation matrix for the Spanish sample

	SPM	PISA	BIS_PN3	BIS_RN3	BIS_RN1	BIS_MF	BIS_RF	BIS_PF	BIS_PN2
SPM	1	.570**	.283**	.148	.381**	.158	-.032	.188*	.171*
PISA		1	.449**	.310**	.457**	.145	-.078	.316**	.298**
BIS_PN3			1	.497**	.557**	.160	.067	.265**	.411**
BIS_RN3				1	.558**	.136	.159	.191*	.421**
BIS_RN1					1	.170*	.191*	.334**	.391**
BIS_MF						1	.157	.217**	.136
BIS_RF							1	−.008	.174*
BIS_PF								1	.110
BIS_PN2									1

*Correlation significant at the .05 level
**Correlation significant at the .01 level

Table 2.9 Correlation matrix for the Latin American sample

	SPM	PISA	BIS_PN3	BIS_RN3	BIS_RN1	BIS_MF	BIS_RF	BIS_PF	BIS_PN2
SPM	1	.586*	.472*	.350*	.416*	.378*	.288*	.257*	.345*
PISA		1	.515*	.408*	.492*	.343*	.206*	.256*	.369*
BIS_PN3			1	.454*	.468*	.332*	.294*	.306*	.387*
BIS_RN3				1	.497*	.305*	.358*	.161*	.413*
BIS_RN1					1	.345*	.276*	.254	.368*
BIS_MF						1	.330*	.264*	.280*
BIS_RF							1	.231*	.234*
BIS_PF								1	.213*
BIS_PN2									1

*Correlation significant at the .01 level

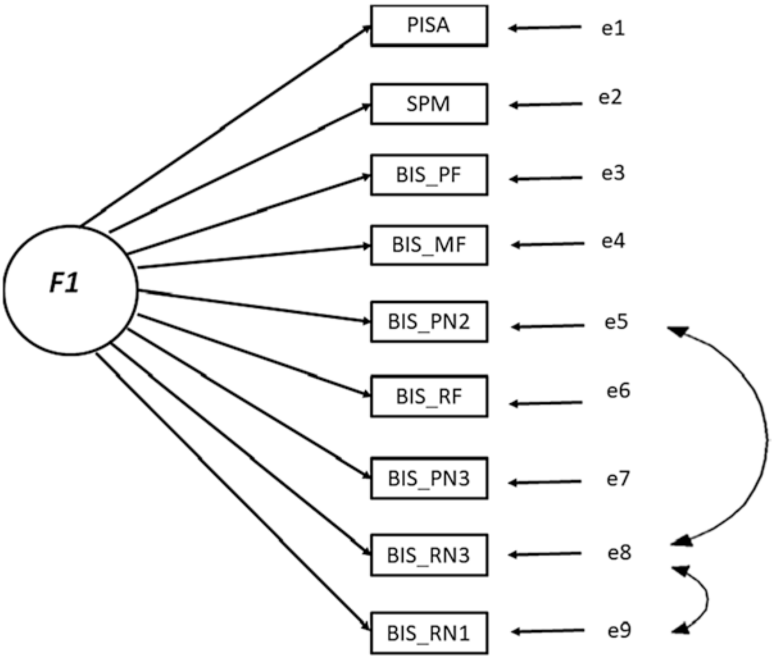


Fig. 2.2 Baseline single factor model for *g*

all Latin American countries in this study, controlling missing data in mean structure analysis (Jamshidian & Bentler, 1999). In cases where there was significant multivariate non-normality in the data, associated test statistics and standard errors may be misleading. To correct for these, the Yuan-Bentler corrections to fit statistics were used (Yuan & Bentler, 2000).

Exploratory factor analysis yielded only one factor with eigen values greater than 1; therefore, we evaluated a single-factor model as shown in Fig. 2.2.

This model fits the data adequately. The scaled Satorra-Bentler $\chi^2 = 254$ $df = 25$, $p = .000$, CFI = .930, RMSEA = .048 (90% confidence interval .042–.053). Modification indices (Lagrange multiplier tests) indicated that no additional parameters would significantly improve the fit.

2.2.3 *Confirmation of Model in Individual Samples*

We fit this model (with added constant for mean structure modeling) to each individual country in this study. Table 2.10 presents the unscaled test statistics for all the countries (generally worse than the scaled statistics). The model fit adequately in all cases. Note the particularly small and potentially unrepresentative sample for Spain and Mexico.

Table 2.10 Model fit parameters for individual countries

	CFI	X^2	*df*	*p*	RMSEA (90% conf)
All countries	.98	283	24	.000	.03(.02, .04)
Argentina	.98	61	24	.000	.04(.02, .05)
Brazil	1.00	52	24	.000	.00
Chile	.99	96	24	.000	.02(.00, .04)
Colombia	1.00	70	24	.000	.00(.00, .03)
Mexico	1.00	28	24	.000	.02
Peru	.99	63	24	.000	.02(.00, .04)
Spain	.92	53	24	.000	.08(.04, .11)

Note: Boundaries of RMSEA confidence intervals could not be computed for Brazilian and Mexican sample

2.3 Conclusion

The all-positive pattern of correlations among diverse cognitive tests found in our study is considered to be evidence of the general nature of human intelligence (i.e., the *g* factor). Robust statistical techniques, such as SEM, which combines factor analysis and multiple regression analysis, confirmed strong unidimensionality rather than the existence of several factors in the general Latin American sample as well as the subsamples (cities). Moreover, the academic experience built up over one century of psychological research permits us to assert that this general ability (general intelligence or *g* factor), measured by psychological tests, correlated well with important social events and life outcomes. Therefore, understanding and measuring the *g* factor will provide information about how well the Latin American society can reason, plan, solve problems, think in abstract, learn rapidly, and comprehend complexities. The next chapters are dedicated to responding to this question.

References

Bentler, P.M. (1985). *Theory and implementation of EQS. A structural equations program*. Los Angeles: BMDP Statistical Software.

Carroll, J. B. (1993). *Human cognitive abilities: A survey of factor-analytic studies*. New York: Cambridge University Press.

Detterman, D. K., & Daniel, M. H. (1989). Correlations of mental tests with each other and with cognitive variables are highest for low-IQ groups. *Intelligence, 13*, 349–359.

Floyd, R. G., Shands, E. I., Rafael, F. A., Bergeron, R., & McGrew, K. S. (2009). The dependability of general-factor loadings: the effects of factor-extraction methods, test battery composition, test battery size, and their interactions. *Intelligence, 37*, 453–465.

Gardner, H. (1983). *Frames of mind: The theory of multiple intelligences*. Nueva York, EUA: Basic Books.

Gottfredson, L. (1997). Why g matters: The complexity of every life. *Intelligence, 24*, 79–132.

Jamshidian, M., & Bentler, P. M. (1999). ML estimation of mean and covariance structures with missing data using complete data routines. *Journal of Educational and Behavioral Statistics, 24*, 21–41.

Jensen, A., & Weng, L. (1994). What is a good g? *Intelligence, 18*, 231–258.

Jensen, A. (2008). Book review. *Intelligence, 36*, 96–97.

Jensen, A. R. (1998). *The g factor*. London: Praeger.

Johnson, W., Bouchard, T. J., Krueger, R. F., McGue, M., & Gottesman, I. I. (2004). Just one g: consistent results from three test batteries. *Intelligence, 32*, 95–107.

Ree, M. J., & Earles, J. A. (1991). The stability of g across different methods of estimation. *Intelligence, 15*, 271–278.

Spearman, C., & Jones, L. W. (1950). *Human ability: A continuation of the abilities of man*. London: Macmillan.

Spearman, C. (1927). *The abilities of man: Their nature and measurement*. London: Macmillan.

Sternberg, R. J. (1985). *Beyond IQ: A triarchic theory of human intelligence*. New York: Cambridge University Press.

Sternberg, R. J. (2003). "My house is a very very fine house"—But it is not the only house. In H. Nyborg (Ed.), *The scientific study of general intelligence. Tribute to Arthur R. Jensen*. Oxford: Pergamon.

Thorndike, R. L. (1987). Stability of factor loadings. *Personality and individual differences, 8*, 585–586.

Yuan, K., & Bentler, P.M. (2000). Three likelihood-based methods for mean and covariance structure analysis with nonnormal missing data. *Sociological Methodology, 30*, 165–200.

Chapter 3
Education, SES, and Intelligence

Abstract Three studies analyzed the effect of education and social variables on intelligence (represented by one cognitive measure and at the *g* level) using samples from the SLATINT Project. The results indicated that intelligence, as measured by one measure (e.g., the SPM or IR test), was slightly influenced by education or the SES of schools. However, when intelligence was represented at the latent level (or *g* factor), the influence of social variables decreased. On the other hand, school performance was primarily influenced by cognitive differences, and secondly by the SES of schools.

3.1 Introduction

Since the nineteenth century, economists have highlighted the role of education in individual and national development. For instance, the prominent British philosopher and economist John Stuart Mill (1806–1873) defined social progress in terms of the increase of knowledge through education in his book, *IV Principles of Political Economy* (available from https://www.gutenberg.org/files/30107/30107-pdf.pdf). Another British economist, Alfred Marshall (1842–1924), addressed the question of how individual investments in education influence the wealth of a nation (Marshall, Keynes, & Guillebaud, 1978). Since this time, hundreds of books and papers have been published demonstrating that education plays an important role in shaping the life opportunities of an individual.

The current consensus is that higher education leads to higher earnings and social status for individuals. The same can be applied to countries. Countries that are more educated produce more wealth than countries that are less educated. Countries that are more educated are more prepared for dealing with the challenges of our modern era. Additionally, it can be said that educated countries produce more technology, innovation, and science (OECD, 2013).

According to the online American business magazine Forbes (www.forbes.com), in 2016, seven of the top ten largest technology companies in the world were located in the USA: Apple, Microsoft, Alphabet, Intel, IBM, Cisco Systems, and Oracle. When considering the top 25 technology companies, and excluding American

C. Flores-Mendoza et al., *Intelligence Measurement and School Performance in Latin America*, https://doi.org/10.1007/978-3-319-89975-6_3

companies, 11 were from China, Taiwan, South Korea, India, Germany, Sweden, and Finland. Together, these companies produce considerable wealth and their nation's economies grow faster than the world's economy. For instance, in 2016, Apple (USA) produced US$ 233 billion in revenue and US$ 53 billion in profit (in 1995, Apple had US$ 11 billion of revenues), while Samsung (South Korea) earned US$ 177 billion in revenue and US$ 16.5 billion in profit (in 2005, Samsung received US$ 70 billion in revenues). Apple and Samsung produced a combined income of 410 billion dollars, which is almost the same produced by countries such as Australia (420.5 billion dollars) or Spain (461.3 billion dollars). In addition, the revenues of Apple and Samsung are greater than the income of countries such as the Netherlands (US$ 322.6 billion), New Zealand (US$ 67.61 billion) or Latin American countries such as Mexico (US$ 224). 3 billion), Argentina (US$ 115.9 billion), Colombia (US$ 76.06 billion), Peru (US$ 60.84 billion) or Chile (US$ 49.52 billion). Despite the fact that high-tech companies and some countries produce almost the same size of revenues, the size of the workforce of high-tech companies (Samsung with 325,680 and Apple with 116,000 employees) is much smaller than the size of the workforce of many countries (for example, Australia with 12 million people). It is an example of how sophisticated human capital increases the performance (and wealth) of technology companies.

To be a high technology (i.e., high tech) company requires certain competencies that are related to higher knowledge and skillsets, especially in the current era of Big Data (behavior prediction through information processing at high volumes and high speeds), IoT (Internet of Things), biotechnology, and Artificial Intelligence/Machine Learning. New jobs are being created, and new (or improved) skills are required. According to the report "The Future of Jobs" published by the World Economic Forum (2016), by 2020, a loss of 7.1 million jobs is expected (70% related to office and administrative roles) due to the disruptive labor market changes provoked by technology. Therefore, it is unsurprising that individuals and governments make massive investments in education. For both individuals and governments, the goal is to attain increased competencies (or cognitive abilities) through education (or training in the case of business), because historically, education and cognitive development have always been correlated. Soon we will see that, while the observed association is correct, there are contradictory results about upskilling (or reskilling) through education.

3.2 Intelligence and Education: Lessons from Differential Psychology

It was reported that in ancient China, specifically the period between the Qin and Han dynasty (200 BC), qualified individuals were recruited and selected for civil service through multiple and extremely rigorous reasoning tasks (Bowman, 1989). For the Chinese empire, it was clear that the existence of individual differences and their examination system sought to identify the best people (those with high levels of knowledge and intelligence) for the bureaucratic service. In the Western culture, the scientific recognition of individual differences only appeared in the nineteenth century, with the birth of Differential Psychology, founded by Sir Francis Galton. Since then, it has been widely accepted that human populations differ (within and between) in their ability to absorb and process information, and this variability is strongly related to the intelligence variability.

There is a large volume of worldwide research in which a positive and statistically significant correlation has been found between school performance and intelligence. According to the report of the American Psychological Association (Neisser et al., 1996)—elaborated on by a team of recognized experts in the field of intelligence—the mean correlation between scores of intelligence tests and scores of school performance tests is .50. Some researchers (Kaufman, Reynolds, Liu, Kaufman, & McGrew, 2012) demonstrated that intelligence and school performance at the latent level is basically the same. Thus, children with high performance in intelligence tests usually tend to process scholastic information better than children with low performance.

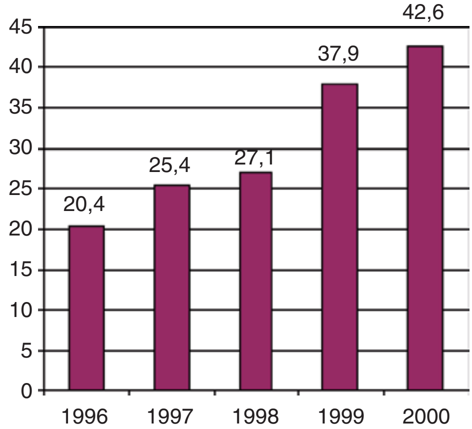
A concrete example would be useful for visualizing the relationship between school performance and intelligence. Figure 3.1 shows two items/questions extracted from the PISA test. The first requires perceptual discrimination (low complexity), and the second requires reasoning (high complexity).

A total of 530 Brazilian students, between 14 and 15 years of age, who were part of the SLATINT sample, were assessed with the PISA test and the Standard Progressive Matrices of Raven or SPM (intelligence test). For the PISA item with low complexity, 96% of the students with SPM score equal to or above +1 standard deviation and 50% of the students with SPM score equal to or below −1 standard deviation responded correctly to this item. For the PISA item with high complexity, 62% of students with high SPM score and 15% of students with low SPM score responded correctly to this item. This is an interesting example of the strong association between cognitive and school performance.

However, as every researcher knows, correlation does not mean causality. Here begins again the classic academic battle between nature and nurture (or genetics × environment). If genetic factors have considerable influence on individual differences in intelligence, as quantitative genetic research has indicated (Bouchard & McGue, 1981; Deary, Johnson, & Houlihan 2009; Lynn & Hattori, 1990; Plomin & DeFries, 1980; Shakeshaft et al., 2015), and if cognitive training has failed to increase intelligence (Melby-Lervåg & Hulme, 2013; Thompson et al., 2013), it is possible to consider that the effect of education on intelligence should be small.

In this regard, the talk given by Professor Douglas Detterman during the 2016 International Seminar "Advances on Intelligence Research: What should we expect from the XXI Century" at the Universidad Complutense de Madrid (video available in https://www.youtube.com/watch?v=A8ycRdy23s0) is quite enlightening. Professor Detterman was the founder of the scientific journal, *Intelligence*, and was its editor-in-chief until 2016. His (controversial) lecture entitled "Education and intelligence: Pity the poor teacher because student characteristics are more significant than teachers or schools," notes that in contrast to multiple innovations in

Total of annual exportation (in millions of *zeds*) of *Zedelandia*, 1996-2000



What the total value (in millions of *zeds*) of the exportation of *Zedelandia* in 1998?

Low complexity

In a pizza restaurant, you can order a basic pizza with two toppings: Cheese and tomato. There are four extra toppings: Olive, ham, salami and mushrooms. Rose wants a pizza with two different toppings.

From how many different combinations Rose can choose?

High complexity

Fig. 3.1 Examples of items from the PISA test and level of complexity

reproduction, habitation, locomotion, eating, and commerce; education has not significantly changed in the last 3000 years. Why? According to Professor Detterman, government investment has always been in schools and teachers, which account for 10% of differences in school performance. Policy makers never focus on students, whose characteristics account for 90% of differences in academic achievement. Detterman's talk was mainly based on the classic Coleman report released in the 1960s (Coleman et al., 1966), in which results indicated that differences within schools are greater than between schools. However, Detterman considered that according to the results of Gamoran and Long (2006) or Heyneman and Loxley

(1983), schools could account for 10% of variance of academic achievement in developed countries, but between 10–40% in developing countries. This observation can be linked to other evidence detected in quantitative genetic research. Recent studies (Turkheimer, Haley, Waldron, & D'Onofrio 2003; Harden, Turkheimer, & Loehlin, 2007; Tucker-Drob & Bates, 2015) observed that differences in environmental and genetic effects follow differences in socioeconomic status (SES) (or genotype-environment interaction), i.e., genetic effects are stronger in high SES schools while environmental effects are stronger in low SES schools. This evidence is important to take into consideration when interpreting results from our SLATINT Project.

3.3 Education in Latin America: How Prepared Is the Region for this New Era?

From a historical perspective, literacy in the Latin American region increased much later than in developed countries. In the mid-nineteenth century, the spread of literacy was extensive in western and northern Europe, achieving over 95% in the mid-twentieth century (only Italy, Poland, and Spain achieved 50% and Portugal 25% literacy rate). In the USA, the rate of literate adults was 80% in 1870 and 95% in 1940. In Canada, the rate of literacy was 83% in 1901 and 95% in 1931. Meanwhile, Argentina, Cuba, and Chile achieved a literacy rate between 35% and 45% at the beginning of the twentieth century. Brazil, Colombia, and Mexico had literacy rates below 30% at this time (United Nations Educational Scientific and Cultural Organization, 2005). The transition from illiterate to literate societies ended only in the last decades of the twentieth century in the Latin America region. Perhaps this is the reason why developed countries differ from Latin American countries in their experience in national and international school assessment.

At the beginning of the twenty-first century, Latin American governments realized the need to evaluate their students. In all global assessments, the results, with some variation, were the same: lower school performance of Latin American students compared to the school achievement of students from developed countries (Organisation for Economic Co-operation and Development, 2005, 2007, 2010, 2014).

3.4 Education and Intelligence: Results from the SLATINT Project

Previously, our SLATINT Project performed two studies that investigated the SES effect on intelligence (or cognitive performance). The first study (Flores-Mendoza et al., 2015) aimed to verify the influence of socioeconomic variables and cognitive performance on PISA scores, and vice versa, verifying the influence of socioeconomic variables and PISA results on the SPM test. For this study, the sample comprised 3724 students between the ages of 14 and 15 years from the cities of Rosario-Argentina, Belo Horizonte-Brazil, Santiago-Chile, Bogotá-Colombia, Madrid-Spain, Mexico City-Mexico, and Lima-Peru. Our descriptive statistics indicated that the variation in PISA scores (Fig. 3.2), similar to the SPM scores (Fig. 3.3), followed social variables, such as type of school (public vs. private), socioeconomic level of school, or parents' education level. The influence of these variables was strongest on the PISA scores compared to the SPM scores. Additionally, the correlation between the PISA test and the SPM test was .582, and this was unsurprising. As previously stated, the literature indicated the existence of this relationship. However, considering that our dataset had a multilevel structure (e.g., students within classes, schools within countries), we performed a generalized linear mixed model. The results indicated 35% PISA variability influenced by changes in the SPM test, while 8.6% variability in the SPM scores was influenced by changes in the PISA scores. In other words, the influence that intelligence (SPM score) had on the PISA score was stronger than vice versa. On the other hand, the socioeconomic status of students had no significant influence on school performance or on cognitive performance, but a school's socioeconomic status had a significant influence. PISA scores varied up to 1.53 times, while SPM scores varied up to 1.04 times, due to changes in the SES of the school.

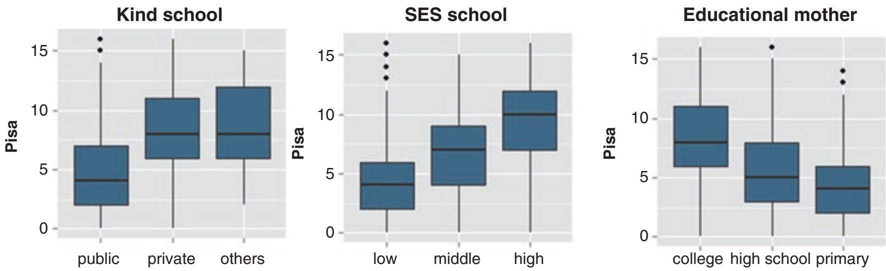


Fig. 3.2 Boxplot of PISA score distribution according to kind of school, school SES, and mother's education level

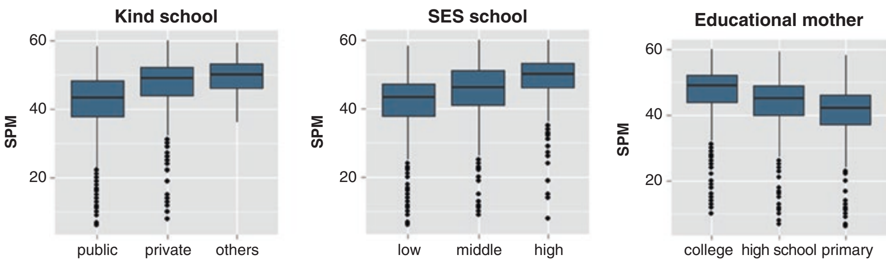


Fig. 3.3 Boxplot of SPM score distribution according to kind of school, SES school, and mother's education level

The second study was related to the inferential reasoning or IR (Flores-Mendoza et al., 2017). The goal was to test the effects of the SES at the individual (students) level and group (school) level on IR. In this study, 2,358 students aged between 14 and 15 years, 52% female, from 52 different schools (44% public) from Argentina, Brazil, Chile, Colombia, and Peru took the IR test (Sisto, 2006). Analysis of covariance between SES student and IR revealed a small correlation ($r = 0.10$, $p < .001$). Chile presented the smallest correlation ($r = 0.04$, $p = 0.63$), and the correlation for other countries ranged from 0.17 to 0.22 (all $p < .001$). However, the SES of the school had a significant effect on IR [$F(2,1944) = 74.68$, $p < .001$, $\eta_p^2 = 0.07$], with higher IR at schools with higher SES, when compared to medium and low SES schools.

The message from both studies seems to be the same: the environment (SES of the school) can be more important than the SES of the family in its influence on student's school performance (and less strong for cognitive performance).

For this book, we consider the variable intelligence at the latent level instead of using a score from only one measure, as we did in previous studies. Again, our main aim was to verify the influence of socioeconomic variables and education (PISA scores) on intelligence (at the latent level), and vice versa. Thus, we analyzed data from 1,303 students enrolled in 32 schools from five Latin American countries (Argentina, Brazil, Chile, Colombia, and Peru). Unfortunately, the Mexican sample was very small and not representative of the school system of this country (i.e., only 66 students from a private school performed the cognitive battery). Table 3.1 shows the average number of students per school (mean = 40.72; min = 15 and max = 111). The average number of students per country was 260.6 (min = 168 and max = 436).

Intelligence was measured through five cognitive measures: the SPM of Raven, BIS_MF, BIS_PN3, BIS_RN3, and BIS_RN1 (see Chap. 1 for details of these measures). The reason why the other three cognitive measures (BIS_RF, BIS_PF, and BIS_PN2) were not considered in this analysis was related to the low reliability and/or low inter-test correlation for some sub-samples (see tables in Chap. 2).

According to our analysis, the latent variable of intelligence was represented by a single factor extracted from the principal axis factoring. This unique factor accounted for 40% of the variance. The independent variables used were: sex, age, kind of school (private and public), SES of students (called SES student), socioeconomic status of schools (called SES school), education level of mother and father, and PISA score.

Regarding SES measures, as stated in Chap. 1, there was no standardized Latin American approach to measuring SES. For this reason, the SLATINT Project elaborated on the estimation of the SES student, based on available resources found at their home (e.g., cable TV, MP3 player, phone, computer, internet, videogames, and

Table 3.1 Descriptive analysis of number of students per school and country

Variables	*N*	Mean	SD	Min.	1°Q	2°Q	3°Q	Max.
School	32	40.72	18.83	15.00	29.00	33.50	50.50	111.00
Country	5	260.60	113.52	168.00	186.00	199.00	314.00	436.00

weekend magazines), and parents' level of education (mother and father). Each item of available resources in the home represented one point. Regarding the education level of parents, the lowest level of schooling was equivalent to primary school and the highest level was college. Schools were classified as low, middle, and high SES by the researcher responsible for data collection in each country. At least two schools were required from each socioeconomic stratum. Samples of schools from Peru and Brazil were randomly selected. In the case of Peru, technicians from the Ministry of Education selected schools based on the SES of the neighborhood where the school was located. In the case of Brazil, the researcher had access to the dataset produced by Soares and Andrade (2006) regarding the distribution of socioeconomic levels of schools located in the city of Belo Horizonte, which permitted the random selection of Brazilian schools for the present study. Samples from Chile, Argentina, and Colombia were non-probability samples, i.e., researchers from these countries selected schools based on their available knowledge of school infrastructure and socioeconomic characteristics of the neighborhood where the school was located. In order to render validity to this classification, researchers were asked to complete a questionnaire with items regarding sanitary and urban conditions of the neighborhood where each school was located (e.g., waste collection system, drainage system, street lighting, etc.), and items regarding school environment (e.g., school instruction time, class size, mathematics instruction time, presence of computers). The points accumulated produced a total score. The correlation between the total score of the questionnaire and the SES school classification was .72 ($p = 0.05$) for Chilean schools and .63 ($p = 0.03$) for Colombian schools, which indicated good validity of the classifications conducted by the researchers. Unfortunately, the Argentinean researcher could not collect information to report. In this case, the obtained correlation between SES school and SES student of .610; positive correlation between SES school and education level of father (.641) and mother (.671) were considered as evidence of positive validity of the SES classification of Argentine schools.

Table 3.2 indicates that, in general, the total sample comprised 50.5% females. The Colombian sample had the highest percentage of males (55.78%) and the Brazilian sample had the highest percentage of females (53.76%). The majority of students (93.4%) were between 14 and 15 years of age. The Chilean sample was the youngest. The Peruvian sample had the highest percentage of private schools (92%), while Colombia (83.42%) had the highest percentage of public schools. Considering the total sample, there were 37.45% high SES school, 28.86% middle SES, and 33.69% of schools with a low SES. Specifically, the Colombian sample had the highest percentage of low SES schools (83.42%); the Argentine sample had the highest percentage of middle SES schools (37.84%), while the Peruvian sample had the highest percentage of high SES schools (63%). In general, 51.65% of fathers and 71.45% of mothers had a college degree.

Considering a statistical description regarding the composition of the samples (Tables 3.2 and 3.3), our sub-sample of the SLATINT Project was definitely not a representative sample, especially the Peruvian sample, which showed the highest percentage of parents with a high educational level and highest mean of SES student. Therefore, extra caution is required when interpreting our results.

Table 3.2 Description of demographic variables per country

Variables		Argentina		Brazil		Chile		Colombia		Peru		Sum	
		N	%	*N*	%	*N*	%	*N*	%	*N*	%	*N*	%
Sex	Female	228	52.29	100	53.76	82	48.81	88	44.22	160	50.96	658	50.50
	Male	208	47.71	86	46.24	86	51.19	111	55.78	154	49.04	645	49.50
Age	13	3	0.69	17	9.14	9	5.36	0	0.00	12	3.82	41	3.15
	14	223	51.15	113	60.75	130	77.38	118	59.30	142	45.22	726	55.72
	15	193	44.27	43	23.12	28	16.67	79	39.70	148	47.13	491	37.68
	16	17	3.90	13	6.99	1	0.60	2	1.01	12	3.82	45	3.45
Type of school	Others	0	0.00	0	0.00	31	18.45	0	0.00	0	0.00	31	2.38
	Private	213	48.85	67	36.02	79	47.02	33	16.58	289	92.04	681	52.26
	Public	223	51.15	119	63.98	58	34.52	166	83.42	25	7.96	591	45.36
SES school	High	142	32.57	96	51.61	52	30.95	0	0.00	198	63.06	488	37.45
	Low	129	29.59	61	32.80	58	34.52	166	83.42	25	7.96	439	33.69
	Middle	165	37.84	29	15.59	58	34.52	33	16.58%	91	28.98	376	28.86
Father Educ. Level	College	190	43.58	99	53.23	105	62.50	21	10.55	258	82.17	673	51.65
	High school	143	32.80	49	26.34	44	26.19	118	59.30	52	16.56	406	31.16
	Primary	103	23.62	38	20.43	19	11.31	60	30.15	4	1.27	224	17.19
Mother Educ. Level	College	292	66.97	131	70.43	139	82.74	73	36.68	296	94.27	931	71.45
	High school	59	13.53	21	11.29	17	10.12	72	36.18	13	4.14	182	13.97
	Primary	85	19.50	34	18.28	12	7.14	54	27.14	5	1.59	190	14.58

Table 3.3 Description of SES student per country

Country	*N*	Mean	SD	Min.	1°Q	2°Q	3°Q	Max.
Argentina	436	13.26	2.11	7.00	12.00	14.00	15.00	16.00
Brazil	186	13.59	2.20	8.00	12.00	14.00	16.00	16.00
Chile	168	13.45	1.75	8.00	12.00	14.00	15.00	16.00
Colombia	199	11.24	1.96	7.00	10.00	11.00	13.00	16.00
Peru	314	14.22	1.58	9.00	14.00	15.00	15.00	16.00

Figure 3.4 shows boxplots of descriptive statistics of the *g* score distributions (or intelligence at latent level) in each sample of Latin American students. The Argentine sample had the highest median value (.02); the Colombian sample had the lowest median value (−.17), while the Brazilian sample showed the highest variability (SD = .91).

Table 3.4 shows descriptive statistics of *g* scores (or intelligence at the latent level) according to each demographic and social variable. Female students demonstrated a negative *g* score (−.11) below the mean, and males had a positive *g* score (.12). Older students had a negative *g* score (−.33) and a higher variability (.91), while younger students had a positive *g* score (.12) and presented less variability (.77). As expected, public schools had a negative *g* score (−.36), but this was accompanied by a higher variability (.86). Low SES schools had the lowest *g* score (−.43)

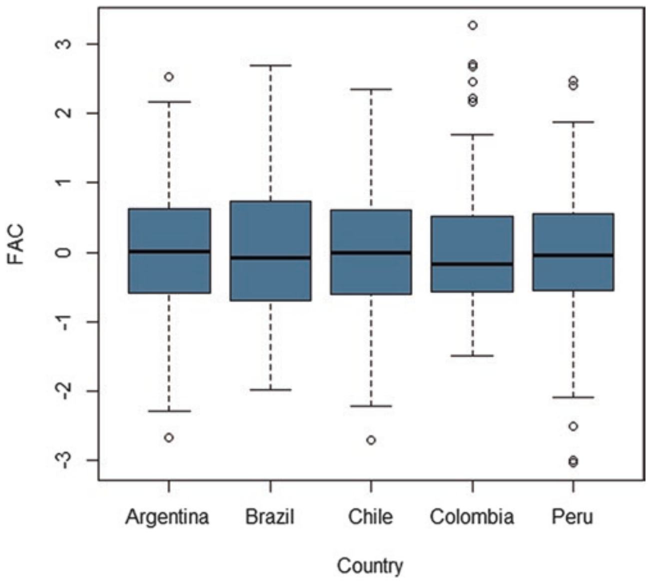


Fig. 3.4 Boxplots of descriptive statistic regarding *g* scores for each sample

Table 3.4 Descriptive statistics of *g* score (or intelligence at the latent level) according to demographic variables

Variables		*N*	Mean	SD	Min.	1°Q	2°Q	3°Q	Max.
Country	Argentina	436	.00	.85	−2.68	−.59	.02	.62	2.52
	Brazil	186	.00	.91	−1.99	−.69	−.08	.73	2.69
	Chile	168	.00	.88	−2.72	−.61	−.02	.61	2.35
	Colombia	199	.00	.84	−1.50	−.57	−.17	.52	3.27
	Peru	314	.00	.86	−3.03	−.56	−.04	.55	2.48
Sex	Female	658	−.11	.83	−3.00	−.68	−.15	.48	2.69
	Male	645	.12	.88	−3.03	−.51	.10	.71	3.27
Age	13	41	.12	.77	−1.13	−.63	.10	.80	1.36
	14	726	.06	.84	−2.51	−.55	.04	.64	2.70
	15	491	−.07	.88	−3.00	−.66	−.14	.55	3.27
	16	45	−.33	.91	−3.03	−.92	−.38	.17	2.09
Type of school	Others	31	.43	.65	−1.15	.06	.38	.79	1.92
	Private	681	.27	.77	−1.80	−.24	.25	.83	2.69
	Public	591	−.33	.86	−3.03	−.90	−.43	.23	3.27
SES school	Low	439	−.43	.87	−3.30	−.99	−.51	.13	3.27
	Middle	376	.40	.75	−2.22	−.48	.50	.57	2.48
	High	488	.35	.77	−1.80	−.20	.37	.93	2.69
Father Educ.	College	673	.21	.82	−1.95	−.34	.20	.79	2.69
	High school	406	−.17	.84	−3.00	−.74	−.21	.40	2.67
	Primary	224	−.32	.87	−3.30	−.85	−.41	.21	3.27
Mother Educ.	College	931	.14	.83	−3.00	−.45	.14	.71	3.27
	High school	182	−.30	.93	−3.30	−.87	−.32	.33	2.22
	Primary	190	−.41	.74	−2.16	−.93	−.50	.13	2.46

and high variability (.87), while high SES schools had the highest *g* score (.35). Students from parents with higher levels of education also had the highest *g* scores.

The nonparametric Spearman correlation between SES student and *g* score was .321 (or .23 Kendall's Tau); while the correlation between SES school and *g* score was .391 (or .306 Kendall's Tau). The same tendency was observed when considering each country, except for the Colombian sample, where no significant correlation was found ($p = .232$) between the SES student and *g* score (Fig. 3.5).

Regarding SES school and *g* score, the strongest association was observed in the Brazilian sample (*rho* = .590; $p = .000$) and the lowest association and non-significant value in the Colombian sample (*rho* = .112; $p = .115$).

Concerning the PISA scores, Table 3.5 shows descriptive statistics for each sample. There were 1,264 students that performed the PISA test (or 97% of the total sample). For the total sample, the mean value was 7.32 (SD = 3.79). Specifically, the Peruvian and the Brazilian sample had the highest means, while the Colombian sample had the lowest mean. The Chilean sample presented the highest variability

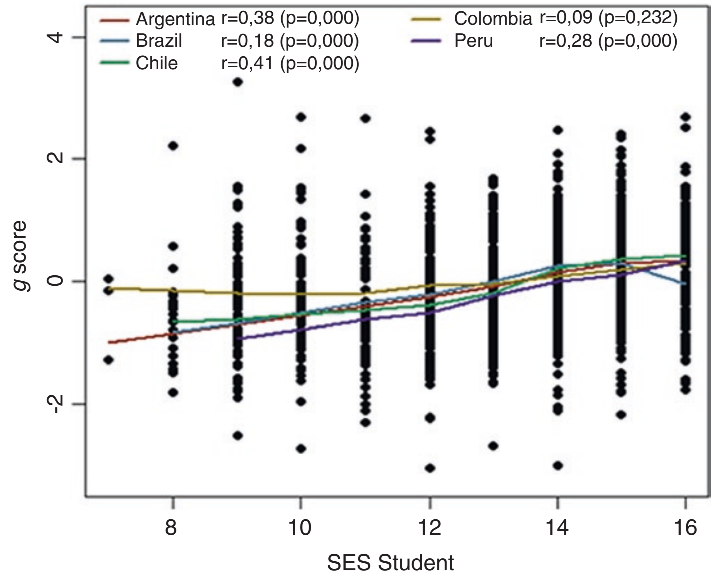


Fig. 3.5 Scatter plot of *g* score vs SES student for each sample

Table 3.5 Descriptive statistics of PISA outcomes for each sample

Variables		*N*	Mean	SD	Min.	1°Q	2°Q	3°Q	Max.
Country	Argentina	435	7.26	3.77	0.00	4.50	7.00	10.00	15.00
	Brazil	152	8.04	3.75	1.00	5.00	8.00	11.00	16.00
	Chile	167	6.56	3.93	0.00	3.00	6.00	10.00	15.00
	Colombia	196	5.85	3.00	0.00	3.50	6.00	8.00	14.00
	Peru	314	8.36	3.84	0.00	6.00	8.00	11.00	16.00
Total		1264	7.32	3.79	0.00	4.00	7.00	10.00	16.00

(SD = 3.93). Males had higher mean scores (7.55; SD = 3.80) than females (7.09; SD = 3.78). Students at 14 years of age had the highest mean score (7.40), and students at 16 years of age had the lowest mean score (6.78). Similar to the *g* score results, private schools presented better performance scores (mean = 8.92) than public schools (mean = 5.32). High SES schools had the highest mean score (9.58), while the low SES schools had the lowest mean score (4.45). Finally, students whose parents had a high education level (college or university) presented the highest mean score, and students whose parents had a low education level (primary school) had the lowest mean score.

The Spearman correlation between the *g* score and PISA score was .649. In order to analyze the influence of all social variables (education, age, sex, SES of students, SES of schools) on *g* score (or intelligence at latent level), we used a generalized linear model, in the same manner as performed previously by our group. For this study, the *g* scores had a normal distribution but the standardized PISA scores presented a slight deviation from normal distribution (Figs. 3.6 and 3.7). For this reason, we used a linear mixed-effect model. This linear mixed model targets the individual (subject-specific models) and it fits the correlation observed in dependent samples (e.g., children within the school and schools within a country). In this model, the mean is dependent on the covariates and the vector of random effects, which can be understood as a heterogeneity produced for factors unknown or unmeasured (Hu, Goldberg, Hedeker, Flay, & Pentz 1998). The results are interpreted in terms of the change for a single individual or individuals, at the same level of the random subject effect; even if the variable is indeed a between-subjects factor. To estimate parameters of the subject-specific model, PQL (Brelow and Clayton, 1993) was used with the function *glmmPQL()* of the *MASS* package (R project).

After selecting variables using the Backward Method, the final model is showed in Table 3.6. Three variables were significant predictors of intelligence at the latent level (or *g* score): PISA score, sex, and age. Effectively, after controlling the vari-

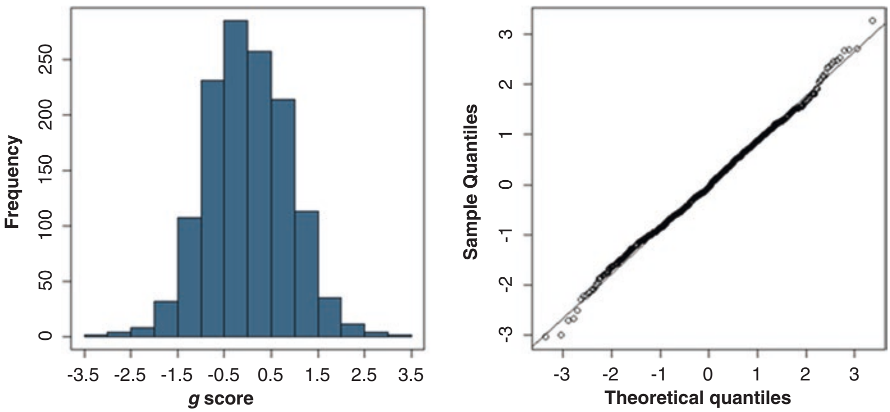


Fig. 3.6 Histogram and Normal Q-Q plot of *g* score

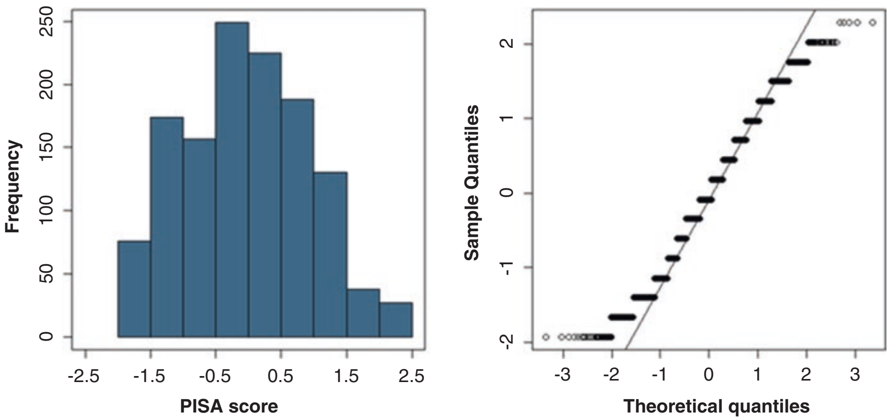


Fig. 3.7 Histogram and normal Q-Q plot of PISA standardized score

Table 3.6 Linear regression with mixed effects to *g* score—Final model

Variables	*β*	s.e(β)	*P*-value	95% CI
Intercept	.23	.11	.046	—
PISA	.52	.02	.000	[.48–56]
Sex = male	—	—	—	—
Sex = female	−.19	.03	.000	[−.26–−.12]
Age = 13	—	—	—	—
Age = 14	−.09	.10	.371	[−.30–.11]
Age = 15	−.19	.11	.078	[−.40–.02]
Age = 16	−.43	.14	.003	[−.71–−.15]

SD (Between) = .237; SD (Within) = .601

ables inserted in the model, there was a significant influence of the PISA score on the latent variability of intelligence (p-value = .000). For each additional standard deviation of the PISA score, an average increase of .52 units (.48; .56) on the mean value of the *g* score is expected. For this sample, the oldest students (16 years old) and female students contributed negatively to predict individual differences in *g* score (−.43 and −.19, respectively). The model explained, with a 95% confidence level, that the *g* score of 71.7% was the variation within schools, and the 28.3% variation was between schools.

Our next step was to verify if the influence of intelligence (at the latent level) on the PISA test resulted in large increases when compared to the influence of the SPM on PISA.

We conducted another multilevel analysis using the PISA score as the dependent variable. The variables were selected using the Backward Method. The final model is shown in Table 3.7. The three variables that are significant predictors of the PISA

Table 3.7 Linear regression with mixed effects to PISA score – Final model

Variables	β	s.e(β)	*P*-value	95% CI
Intercept	−.79	.16	.000	—
g score	.57	.02	.000	[.52–.61]
SES indiv.	.02	.01	.035	[.00–.05]
SES school = low	—	—	—	—
SES school = middle	.51	.13	.000	[.26–.75]
SES school = high	.82	.12	.000	[.58–1.06]

SD (Between) = .245; SD (Within) = .633

score were intelligence at latent level (or *g* score), SES of students, and SES of schools.

There was a significant influence of intelligence at the latent level (or *g* score) on PISA score (*p*-value = .000). For each additional standard deviation to the mean *g* score, an average increase of .57 units [.51–.61] in the mean PISA value could be expected. Additionally, there was an influence of SES of students for the PISA score (*p*-value = .035). For each additional unit in SES of students, an average increase of .02 units [.00–.05] in the mean PISA value could be expected. Students enrolled in high SES schools scored an average value of .82 units higher than students enrolled in low SES schools. Students enrolled in middle SES schools scored an average value of .51 units higher than students enrolled in low SES schools. Students enrolled in high SES schools had an average value of .31 higher than students enrolled in middle SES schools. The model explained, with a 95% confidence level, that 72.1% of variation happened within schools, and a 27.9% variation was observed between schools.

In order to visualize which variables showed the greatest and smallest effect on intelligence (or *g* score) and PISA scores, the following strategy was implemented: (1) If the variable was categorical, the largest Beta was used; and (2) if the variable was numerical, Beta was multiplied by the variation range. In the present study, scores of *g* and PISA were standardized, where the minimum PISA value was −1.93 and the maximum was 2.29, thus the variation range for PISA was 4.22. In the case of *g,* the minimum value was −3.03 and the maximum value was 3.27, thus the range of variation for the *g* factor was 6.30. Considering these values and the final models, Table 3.8 was generated. For the *g* score, PISA had a greater effect, while sex had a smaller effect. For the PISA test, the *g* score had a greater effect, whereas the SES student had a smaller effect. The SES school only had an impact on the PISA test and not on intelligence.

As mentioned before, in a previous study (Flores-Mendoza et al., 2015), we found that SPM scores could vary at a maximum of 1.42 times due to PISA changes, and 1.04 times due to SES school changes. On the other hand, PISA scores could vary at a maximum of 7.79 times due to SPM changes, and a maximum of 1.53 times due to SES school changes. Taken together, intelligence, as measured by the SPM test, was less sensitive than the PISA test to the influence of social variables such as the SES of schools. However, in the present study, the influence of social variables decreased when intelligence was represented at the latent level.

Table 3.8 Summary of maximum effect of the significant predictor variables on intelligence (or *g* score) and PISA test

Variable		Max. effect
Linear regression with mix effects for *g* score	Intercept	.23
	PISA	2.19
	Sex	−.19
	Age	−.43
Linear regression with mix effects for PISA	Intercept	−.79
	g score	3.59
	SES indiv.	.02
	SES school	.82

3.5 Conclusion

Our results obtained in the three studies were quite robust in demonstrating that: (1) individual cognitive differences had a stronger influence on school performance compared to vice versa; (2) individual cognitive differences influenced school performance more strongly than social variables did; (3) variations in the school environment (SES school) better explained school performance compared to family environment (SES student); and (4) social variables were not strong predictors of cognitive differences. Our results replicated those found in more than a century of investigations of Differential Psychology. Policy makers in education, especially from developing countries, should pay attention to these studies.

References

Bouchard, T. J., Jr., & McGue, M. (1981). Familial studies of intelligence: A review. *Science, 212*, 1055–1059.

Bowman, M. L. (1989). Testing individual differences in ancient China. *American Psychologist, 44*, 576–578.

Breslow, N. E., & Clayton D. G. (1993). Approximate inference in generalized linear mixed models. *Journal of the American Statistical Association, 88*, 9–25.

Coleman, J. S., Campbell, E. Q., Hobson, C. J., McPartland, J., Mood, A. M., Weinfeld, F. D., & York, R. L. (1966). *Equality of educational opportunity*. Washington, DC: Government Printing Office.

Deary, I. J., Johnson, W., & Houlihan, L. M. (2009). Genetic foundations of human intelligence. *Human Genetics, 126*, 215–232.

Flores-Mendoza, C., Mansur-Alves, M., Ardila, R., Rosas, R. D., Guerrero-Leiva, M. K., Maqueo, M. E. L.-G., Gallegos, M., …León, A. B. (2015). Fluid intelligence and school performance and its relationship with social variables in Latin American samples. *Intelligence*, 49, 66–83. doi: https://doi.org/10.1016/j.intell.2014.12.005.

Flores-Mendoza, C., Saraiva, R. B., Câmara, G. C. B., Lopes, W. M. G., Passos, A. P. C. P., Gama, A. M. V. P., … Reategui, N. (2017). Socioeconomic environment effect on inferential reasoning of Latin American Students. *Revista de Salud Mental*, 40, 183–190.

Gamoran, A., & Long, D. A. (2006). *Equality of educational opportunity: A 40-year retrospective* (WCER Working Paper No. 2006-9). Madison: University of Wisconsin–Madison, Wisconsin Center for Education Research. Retrieved [December 09, 2017] from https://wcer.wisc.edu/publications/year/2006http://www.wcer.wisc.edu/publications/workingPapers/papers.php

Harden, K. P., Turkheimer, E., & Loehlin, J. C. (2007). Genotype by environment interaction in adolescents' cognitive aptitude. *Behavior Genetics, 37*, 273–283. https://doi.org/10.1007/s10519-006-9113-4

Heyneman, S. P., & Loxley, W. A. (1983). The effect of primary school quality on academic achievement across twenty-nine high- and low-income countries. *American Journal of Sociology, 88*, 1162−1194.

Hu, F. B., Goldberg, J., Hedeker, D., Flay, B. F., & Pentz, M. A. (1998). Comparison of population-averaged and subject-specific approaches for analyzing repeated binary outcomes. *American Journal of Epidemiology, 147*, 694–703. Retrieved from http://aje.oxfordjournals.org/content/147/7/694.short.

Kaufman, S. B., Reynolds, M. R., Liu, X., Kaufman, A. S., & McGrew, K. S. (2012). Are cognitive g and academic achievement g one and the same g? An exploration on the Woodcock–Johnson and Kaufman tests. *Intelligence, 40*, 123–138.

Lynn, R., & Hattori, K. (1990). The heritability of intelligence in Japan. *Behavior genetics, 20*, 545–546. https://doi.org/10.1007/BF01067719

Marshall, A., Keynes, J. M., & Guillebaud, C. W. (1978). *Obras escogidas*. DF Mexico: Fondo de Cultura Economica.

Melby-Lervåg, M., & Hulme, C. (2013). Is working memory effective? A meta-analytic review. *Development Psychology, 49*, 270–291. https://doi.org/10.1037/a0028228

Neisser, E.U., Boodoo, G., Bouchard, T., Boykin, A., Brody, N., Ceci, S., …Urbina, S. (1996): Intelligence: Knowns and unknowns. *American Psychologist,* 51, 2, 77–101.

Organisation for Economic Co-operation and Development—OECD (2007). *PISA 2006: Science competencies for tomorrow's world: Vol. 1 Analysis*. Retrieved from http://www.oecd-ilibrary.org/education/pisa-2006_9789264040014-en.

Organisation for Economic Co-operation and Development—OECD (2010). *PISA 2009 results: What students know and can do — Student performance in reading, mathematics and science (Vol. I)*. https://doi.org/10.1787/9789264091450-en.

Organisation for Economic Co-operation and Development—OECD (2013). *PISA 2012 Results in focus: What 15-years-old know and what they can do with what they know.* Retrieved from http://www.oecd.org/pisa/keyfindings/pisa-2012-results-overview.pdf.

Organisation for Economic Co-operation and Development—OECD. (2014). *PISA 2012 results: What students know and can do*. Retrieved from http://www.oecd-ilibrary.org/education/pisa-2012-results-what-students-know-and-can-do-volume-i-revised-editionfebruary-2014_9789264208780-en.

Organisation for Economic Co-operation and Development—OECD. (2005). *PISA 2003 Technical Report.* Retrieved from http://www.oecd-ilibrary.org/education/pisa-2003-technical-report_9789264010543-en.

Plomin, R., & DeFries, J. C. (1980). Genetics and intelligence: Recent data. *Intelligence, 4*, 15–24.

Shakeshaft, N. G., Trzaskowski, M., McMillan, A., Krapohl, E., Simpson, M. A., Reichenberg, A., … Plomin, R. (2015). Thinking positively: The genetics of high intelligence. *Intelligence, 48*, 123–132.

Sisto, F. F. (2006). *Teste de raciocínio inferencial*. São Paulo: Vetor Editora Psicopedagógica.

Soares, J. F., & Andrade, R. J. (2006). Nível socioeconômico, qualidade e eqüidade das escolas de Belo Horizonte [Socioeconomic status, quality and equity in the schools of Belo Horizonte]. *Ensaio: Avaliação de Política Pública de Educação, 14*, 107–126. Retrieved from http://www.scielo.br/pdf/ensaio/v14n50/30410.pdf.

Thompson, T. W., Waskom, M. L., Garel, K.-L. A., Cardenas-Iniguez, C., Reynolds, G. O., Winter, R. … Gabrieli, J. D. (2013). Failure of working memory training to enhance cognition or intelligence. *PLoS ONE,* 8, e63614. doi: https://doi.org/10.1371/journal.pone.0063614.

Tucker-Drob, E. M., & Bates, T. C. (2015). Large cross-national differences in gene × socio-economic status interaction on intelligence. *Psychological Science, 27*, 138–149. https://doi.org/10.1177/0956797615612727

Turkheimer, E., Haley, A., Waldron, M., & D'Onofrio, B. (2003). Socioeconomic status modifies heritability of IQ in young children. *Psychological Science, 14*, 623–628.

United Nations Educational Scientific and Cultural Organization. (2005). *Literacy for life. efa global monitoring report*. France: UNESCO.

World Economic Forum. (2016). *The future of jobs. Employment, skills and workforce strategy for the fourth.* Retrieved 9 December 2017, from https://www.weforum.org/reports/the-future-of-jobs.

Chapter 4
Intelligence, Problem Solving, and Creativity

Abstract In this chapter, notions of psychometric intelligence and cognitive psychology were used to analyze individual differences in the ability to execute cognitive processes. Specifically, the performance of good and poor problem solvers through the analysis of the types of errors in the SPM test were studied. Additionally, the relationship between creativity and intelligence was analyzed in middle-low and high cognitive performers.

4.1 Problem Solving

In human behavior research, the use of the term "cognitive" was prevalent in the 1950s and 1960s. This term was associated with internal events, such as "thinking," "symbolic representation," or "ideational system." Because of the increased use of the term, the "cognitive" label was elevated to the status of "Cognitive Science" (Hunt, 1989). Unfortunately, at that time, psychometricians were concerned with the factorial analysis of psychological tests, while cognitive psychologists were concerned with matters of thought (Butcher, 1968). Only recently have both research fields begun to look more closely at each other and work together. From an interdisciplinary point of view, the general focus is to achieve a scientific understanding of how the human mind works and how it relates to intelligence.

John Anderson, professor at the Carnegie Mellon University and renowned cognitive psychologist, who specializes in the cognitive processes involved in solving problems wrote, " … all cognitive activities are fundamentally problem solving in nature" (Anderson, 1990; p. 221). Based on classic literature on cognitive psychology (Greeno & Simon, 1988; Vosniadou, 1988), Anderson presented the most frequent problem-solving methods, such as The Difference-Reduction Method, Means-Ends Analysis, Working Backward, Problem Solving by Analogy, Production Systems, Formalism, Representation, and Set Effects. All these methods use three fundamental cognitive processes: definition of the wanted goal (initial state or initial situation of the problem solver); decomposition of the problem/situation into sub-goals (intermediate state or sub-tasks setting); and selection of operators to achieve sub-goals. As the operators change the initial state into another state, the challenge

C. Flores-Mendoza et al., *Intelligence Measurement and School Performance in Latin America*, https://doi.org/10.1007/978-3-319-89975-6_4

for the problem solver is to identify the needed sequence of changes that drive the initial state to the goal state.

Anderson recognized that there is no method that can explain what steps a problem solver takes in order to achieve the goal state. In this sense, instead of describing algorithms (procedures for solving a problem, e.g., math algorithms that lead to the solution of an equation), all cognitive methods describe heuristics that *probably* lead to a solution.

Usually, problem-solving strategies are studied from an experimental design using well-defined tasks, such as Missionaries-Cannibals (three missionaries and three cannibals must cross a river in a boat where only two passengers can be transported) or Tower of Hanoi (presentation of three pegs and six disks; each disk must be transferred to either of the two other pegs, one at a time, and a larger disk can never be placed on a smaller one). These problems can be solved by defining the sub-goals, i.e., by breaking the problem into smaller parts. This relationship with intelligence has been weak to moderate (Vernon & Strudensky, 1988).

Another kind of problem, referred to as "Complex Problem Solving, (CPS) has been studied (Wustenberg, Greiff, & Funke, 2012). Unlike traditional and well-structured problems, CPS tasks demand that the solver interacts with unknown and dynamically changing environments (e.g., management of simulated cities). A meta-analysis conducted by Stadler, Becker, Godker, Leutner, and Greiff (2015) that included 47 studies, indicated a substantial correlation (.433) between CPS and psychometric intelligence.

Another method for understanding the individual's overall ability is to analyze incorrect response choices in intelligence tests (Chuderski, 2015; Kunda, Soulières, Rozga, & Goel, 2013, 2016; Van Herwegen, Farran, & Annaz, 2011). This strategy, typically used in information-processing research, could be applied to differential psychology, due to the chance that the probability of choosing different incorrect answer alternatives could vary according to ability, i.e., different incorrect items could be associated with different ability levels (Gunn & Jarrold, 2004; Van Herwegen et al., 2011). Some efforts have been made following this method. The intelligence test that, besides the correct choices, also provides information from incorrect choices is the Progressives Matrices of Raven (Raven, Raven, & Court, 2000), specifically the Coloured Progressive Matrices (CPM) and the Advanced Progressive Matrices (APM). However, the third version, called the Standard Progressive Matrices (SPM), does not provide information on error analysis. This is a considerable limitation for cognitive and differential psychology insofar as the SPM test is the measure most used in intelligence research all over the world. Kunda et al. (2013, 2016) synthesized the classification of error types provided by the CPM and APM tests, as follows:

- Type I: Incomplete correlated errors. This kind of error refers to the "almost correct answer." The answer alternative presents the elements of the correct answer, but they are not sufficient. Alternatives 2 and 6 from Fig. 4.1 are examples of this type of error.
- Type II: Repetition errors. Here the respondent chooses the alternative answer that is similar to the matrix entry adjacent to the blank space of the matrix. Alternatives 5 and 7 (Fig. 4.1) are examples of this type of error.

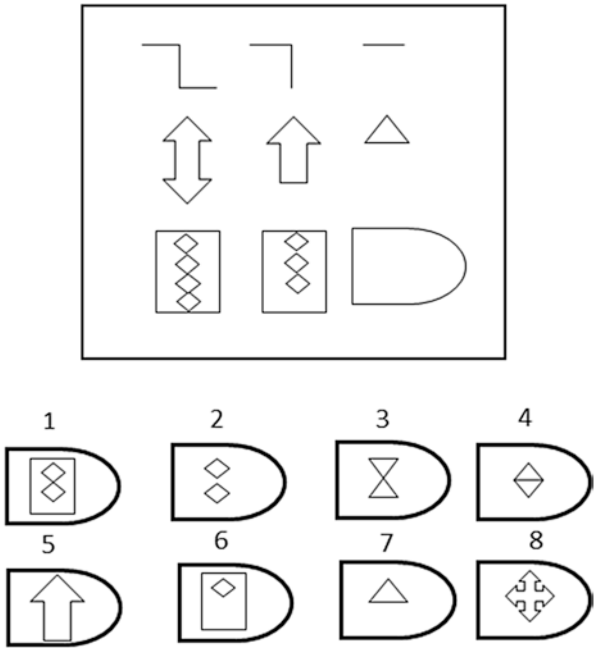


Fig. 4.1 Prototypical problem from the SPM test

- Type III: Differences errors. These types of error refer to the selection of the alternative that stands out among all available alternatives. Filled distractors (all black or all white) or those that have quite differentiated elements/shape can guide the selection of this type of error. Alternative 8 from Fig. 4.1 is an example of this kind of error.
- Type IV: Wrong principle errors. Here the respondent chooses alternatives that contain some elements of the correct answer, but these elements, besides being insufficient, follow an incorrect rule. Alternatives 3 and 4 from Fig. 4.1 are examples of this kind of error.

Obviously, Fig. 4.1 shows an example of an item with answer alternatives that are easy to classify using the taxonomy of errors previously presented. Using them on real items of the SPM test is not an easy task. The main problem is that some answer alternatives from the SPM test could be classified into two (even three) kinds of errors. Kunda et al. (Kunda et al., 2013, 2016) tried to use this taxonomy in all items of the SPM test to analyze information processing of a group of typically developing individuals and individuals with autism. In addition, Vodegel Matzen, Van der Molen, and Dudink (1994) analyzed answer choices from a group of SPM items from a large sample of children; however, they used a taxonomy of errors slightly different to those employed by Kunda et al. (incomplete errors/confluency of ideas, wrong principle error, repetition, and additional elements). Additionally, they analyzed answer choices according to ability level (above average, average, and below average). Both studies used raters to verify the reliability of the taxonomies employed. Kunda et al. (Kunda et al., 2013, 2016) obtained a high agreement between raters (82% and 95%, after a negotiation phase between the two raters). Vodegel Matzen et al. (1994) obtained 71.5% of inter-rater agreement. As result**,** Kunda et al. found a high proportion of Type IV errors (Wrong Principle) followed by Type II errors (Repetition), and Type III errors (Difference). The lowest proportion was Type I errors (Incomplete Correlate). Similar results were obtained by Babcock (2002) using the APM version. Considering clinical diagnoses, Kunda et al. found that children and adults with autism made more Type II errors (Repetition) than individuals without a clinical diagnosis. Vodegel-Matzen et al. found, independent of ability level, a high proportion of Type I errors (Incomplete Correlate), followed by Type IV errors (Wrong Principle), Type II errors (Repetition), and errors called Additional Elements (similar to Type III errors). However, Type I and Type II errors better reflected children of high and low performance.

What do the different types of errors signify in terms of cognitive processing? We are inclined to accept the argument of Vodegel-Matzen et al. that Type I and Type IV errors are attempts to solve the problem as the examinee considers all the elements from the alternatives available and tries to discriminate information that is relevant to the final solution. On the other hand, Type II and Type III errors are decisions that involve less cognitive effort, especially Type III errors due to the indifference of the examinee towards elements presented in the matrix.

For this chapter, we decided to analyze the performance of problem solvers in PISA items of high and low complexity according to their cognitive ability (Sect. 4.1) using psychometric analysis. Following this, we analyzed the types of errors executed by good and poor problem solvers (Sect. 4.2). For both analyses, we used the SPM test, the psychometric measure most commonly used in cognitive and differential psychology research.

4.1.1 High and Low Problem Solving Ability Based on the g *Factor*

In order to obtain the high and low ability group, we saved factor scores from the unique factor (here considered as a cognitive *g* factor) extracted by principal axis factoring of cognitive measures administered to the SLATINT sample (see Chap. 2) and then we divided the factor score into quartiles. Quartile 1 would be Q1 (low cognitive ability) and Quartile 4 would be Q4 (high cognitive ability).

The next step was to identify high difficulty items of the PISA test and to verify the proportion of correct answers for these items achieved by the high and the low cognitive ability groups. The short version PISA test, as explained in Chap. 1, contained 16 items. The statistical procedure named Categorical Principal Components Analysis (acronym CATPCA), which runs on the Statistical Package for the Social Sciences (acronym SPSS), indicated two factors in this short version PISA test that explained 33.6% of the variance. However, while the first dimension had an acceptable internal consistency coefficient (Cronbach's alpha of 0.801; 26.4% of explained variance), the second dimension had no internal consistency (Cronbach's alpha of

0.07). Additionally, a confirmatory factor analysis, using MPlus 7.0, indicated that a dimension accounted for the correlation between PISA items. Fit statistics were: RMSEA = 0.035; CFI = 0.949; TLI = 0.940. Thus, the PISA test was considered as a relatively unidimensional measure, and we conducted an IRT analysis of two parameters, using MPlus software.

The most difficult items in the PISA test were identified as item 1, item 9, item 16, and item 5, with a difficulty parameter (in decreasing order) of 2.226, 1.619, 1.495, and 1.211, respectively. A simple way of observing the difference between an easy and a difficult item is by observing the item characteristic curve (ICC) provided by the IRT. Figure 4.2 depicts the ICC for items 1, 9, 16, and 5 (difficult items) and items 10 and 14 (easy items). As an individual's trait level increases, the probability of endorsing an item also increases. For instance, for easy items (10 and 14) an underlying trait level (Theta) of −0.5 would be enough to achieve 50% of probability for endorsing these items. For difficult items, such as items 16 and 5, a trait level (Theta) of 2.0 would be necessary to achieve 50% of probability of endorsing these items.

The most difficult PISA items (for the sample of the SLATINT Project) are described below.

Item 1 asked examinees to calculate the best possible time for two students from different countries to talk online, knowing that the time zone between the two countries was 9 hours and they could not talk during school hours (9:00 AM to 4:30 PM) and bedtime (11:00 PM to 7:00 AM). This problem is not hard to solve since the time available to chat online was quite restricted. Whatever the country, the student could not talk in the afternoon after school, for example at 5:00 PM, because in the other country the student would already be sleeping (1:00 AM). Thus, the remaining option would be to talk in the morning. The only available time would be at 8:00 AM, when the student from the other country would be free to talk as it would be

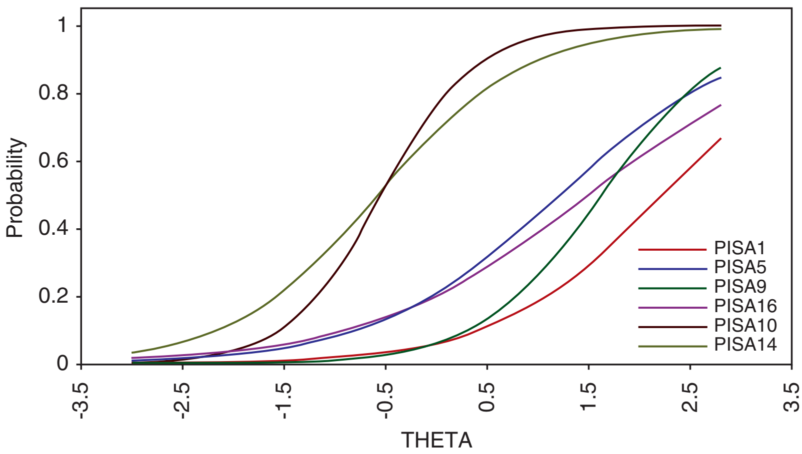


Fig. 4.2 ICC for items 1, 9, 16, and 5 (high complexity) and items 10 and 14 (low complexity)

Table 4.1 Percentage of problem-solvers with high (Q4) and low (Q1) cognitive ability who responded correctly to the most difficult PISA items

	Item 1		Item 9		Item 16		Item 5	
Sample	Q1	Q4	Q1	Q4	Q1	Q4	Q1	Q4
SLATINT	7.7	26.3	3.4	35.7	15.0	44.5	12.6	51.4
ARG	6.2	38.8	4.8	47.0	13.0	47.0	14.4	44.9
BR	20.9	40.0	4.7	40.0	32.6	54.3	9.3	65.7
CHI	0.0	23.8	1.9	38.1	13.2	52.4	3.8	42.9
COL	7.1	8.3	2.9	4.2	17.2	20.8	14.3	25.0
PE	0.0	19.9	0.0	36.4	10.5	39.7	5.2	56.9

Note: *ARG* Argentina, *BR* Brazil, *CHI* Chile, *COL* Colombia, *PE* Peru, *SLATINT* total Latin-American sample

5:00 PM for him. This item was correctly answered by 7.7% of Latin American students of our sample with low cognitive ability (Q1) and 26.3% of students with high cognitive ability (Table 4.1).

Item 9 asked examinees to apply a simple fraction formula [n/P = 140] to find the length of a person's step, where n represented the number of steps per minute and P was the length of the step in meters. The question was: if Hector walks 70 steps per minute, what is the length of his step? The only action the student needed to do was divide the numerator by 140. This item was answered correctly by 3.4% of Latin American students of low cognitive ability (Q1) and 35.7% of students of high cognitive ability (Table 4.1).

Item 16 asked examinees to calculate the average weight of fallen pieces (n = 1500) in the Pacific Ocean from a space station (total weight = 143,000 kg) after it lost 80% of its structure in the atmosphere. First, the student had to calculate the weight of the space station after 80% of its structure was burned in the atmosphere (143,000–114,400 = 28,600) and then divide the remaining weight by 1500 pieces that fell into the Pacific Ocean (28,600/1500 = 19 kg per piece). This item was answered correctly by 15% of Latin American students of low cognitive ability (Q1) and 44.5% of students of high cognitive ability (Table 4.1).

Item 5 asked examinees to calculate the average of five school exams. This item was answered correctly by 12.6% of Latin American students of low cognitive ability (Q1) and 51.4% of students of high cognitive ability.

The observations that can be deduced from Table 4.1. are as follows. The first observation, as expected, is the solid relationship between cognitive ability and the ability to solve problems. A low percentage (9.7%) of students from the group with low cognitive ability and a greater percentage (39.5%) of students from the group with high cognitive ability solved the most difficult PISA items. The second observation refers to the low quality of the education system in Latin America. None of the supposedly "difficult" items demanded high or special knowledge. The items required basic operational knowledge of arithmetic, fractions, percentage, and averages. Despite the high cognitive ability, the percentage of Latin American adolescents aged between 14 and 15 years who correctly solved the four items ranged between 26.3% and 51.4%. The performance for item 5 is the most revealing, demonstrating the low quality of teaching (or low cognitive environment) in Latin America. This item only asked examinees to calculate the mean of five school exams; however, only half of the students (51.4%) with high cognitive functioning were able to answer this question correctly.

Regarding Mexico, unfortunately there was insufficient data to estimate the *g* factor. However, considering the strong association between the *g* factor and the SPM test (0.646), we used the raw score of the Mexican sample and converted it to a common scale (*z*-score) with an average of zero and a standard deviation of one. As expected, the results for the Mexican sample were similar to previous results (Table 4.2).

Another simpler way to observe the effect of environment on the capacity of problem solving is by comparing the percentage of problem solvers with high cognitive ability (Q4) enrolled in schools of low and high SES. Table 4.3 shows the results.

Before forming any conclusion regarding Table 4.3, it was necessary to check if the cognitive ability that was elevated (Q4) was similar between groups enrolled in schools of low and high SES. An independent-sample *t*-test was conducted to compare the *g*-factor score for students of high performance (Q4) who were enrolled in schools of low and high SES. There was no significant difference in *g*-scores for high-performing students from low SES schools ($M = 1.142$; SD = 0.610) and high-performing students from high SES schools [$M = 1.186$; SD = 0.461; $t(254) = -0.455$; $p = 0.649$]. These results indicated that differences in the percentage of high-performing students responding correctly to the hardest items of the PISA test were not associated with differences in *g*. In order to verify if the differences between groups were statistically significant, a Chi-square test of independence was calculated comparing the frequency of high performers enrolled in low and high SES schools who responded correctly to each item. Significant interactions were found for item 1 [$X^2(1) = 9.098$, $p = 0.003$], item 9 [$X^2(1) = 12.771$; $p = 0.000$], item 16

Table 4.2 Percentage of Mexican problem solvers of high (Q4) and low (Q1) cognitive ability (based on the SPM test) who responded correctly to the most difficult PISA items

Items	Q1	Q4
Item 1	2.8	19.0
Item 9	6.4	38.4
Item 16	0.9	28.7
Item 5	16.5	42.1

Table 4.3 Percentage of Latin American problem solvers with high cognitive ability (*g* score at Q4) from schools of low and high SES who responded correctly to the most difficult PISA items

High *g*—Low SES school ($n = 28$)				High *g*—High SES school ($n = 228$)			
Item 1	Item 9	Item 16	Item 5	Item 1	Item 9	Item 16	Item 5
3.7	7.4	18.5	22.2	31.4	42.9	51.3	56.2

[$X^2(1) = 10.404$; $p = 0.001$], and item 5 [$X^2(1) = 11.164$; $p = 0.001$]. These results indicated that more high performers enrolled in high SES schools were likely to get correct answers than high performers enrolled in low SES schools. This situation deserves the attention of the Latin American education policy makers.

4.1.2 Do Good Problem Solvers Make Different Types of Errors Compared to Poor Problem Solvers?

In order to analyze differences in problem solving of Latin American students through error analysis, items from the SPM were used in the following way:

(a) Division of Latin American sample into high and low performers and identification of high complexity items.
(b) Submission of the group of hardest items to SPM test experts. The raters indicated the type of error represented by each alternative option for each item (there are eight answer alternatives for each item).
(c) Analysis of agreement among raters.
(d) Descriptive statistic of error type made by each group of performers.

There is no clear conclusion about the dimensionality or uniqueness of the SPM test (Mackintosh & Bennett, 2005). This information was useful and necessary to divide groups into high and low performance, since the test's items represented a unique factor. We performed categorical principal component analysis using the SPSS software (version 20). Nine factors were obtained with eigenvalues above 1, which explained 38.1% of the variance. However, only two dimensions had an acceptable internal consistency coefficient (Cronbach's alpha) equivalent to 0.911 for the first dimension and 0.693 for the second dimension. Our goal was to identify a group of items representing just one dimension. Thus, the observation of the coordinates for each item in relation to the centroid (0,0) indicated 16 items (A12, B12, C6, C7, C8, C10, C11, E1, E2, E3, E4, E5, E6, E7, E8, and E9) with a high mean coordinate, i.e., a set of items with a significant contribution to the principal component. After removing this group of items, the proportion of variance explained by the first dimension was 28.7% with an acceptable consistency coefficient ($\alpha = 0.835$). The second dimension did not have an acceptable consistency coefficient ($\alpha = 0.127$),

Table 4.4 Summary of categorical principal component results from a set of 16 items of the SPM test with high mean coordinate

		Variance accounted for	
Dimension	Cronbach's alpha	Total (Eigenvalue)	% of Variance
1	.835	4.596	28.725
2	.127	1.139	7.12
Total	.881	5.735	35.845

as shown in Table 4.4. Additionally, a Confirmatory Factor Analysis (CFA) was conducted to test unidimensionality. The results indicated that a model of one factor had acceptable fit to the data [CFI = 0.932; TLI = 0.922; RMSEA = 0.044].

After verifying reasonable unidimensionality of the SPM test with 16 items, the next step was to identify the difficulty level of the selected items. We calculated the difficulty of items based on procedures from the CTT (Classic Test Theory), i.e., the proportion of individuals who correctly answer or pass a dichotomous item (focus on test-level information); and based on IRT-2P (Item Response Theory—two parameters), i.e., formulation of the probabilistic distribution of examinees' success at the item level (focus on the item-level information). CTT item difficulty with IRT-based item difficulty estimates (derived from two-parameter IRT models) demonstrated an extremely high correlation ($r = 0.989$). According to these analyses, items E9, E8, and E7 were the most difficult items, while C7, C6, and E1 were the easiest items. Figure 4.3 depicts the ICC for both item types (difficult and easy).

The three most difficult items were sent to four raters with extensive experience in the use of the SPM test. The judges independently rated each wrong answer alternative (seven in total) for each of the three items (7 × 3 = 21 wrong answer alternatives assessed by each rater). There was consistent and complete uniform agreement among raters for items E8 and E9, but not for E7. In this case, the ICC was calculated using the SPSS statistical package version 20 (SPSS Inc., Chicago, IL, USA). As our raters were not randomly chosen from a larger population of possible raters, the ICC estimate was calculated based on a mean-rating ($k = 4$), absolute-agreement, two-way mixed-effects model. The results indicated an agreement of 0.847. Nevertheless, while this value is considered as a good reliability

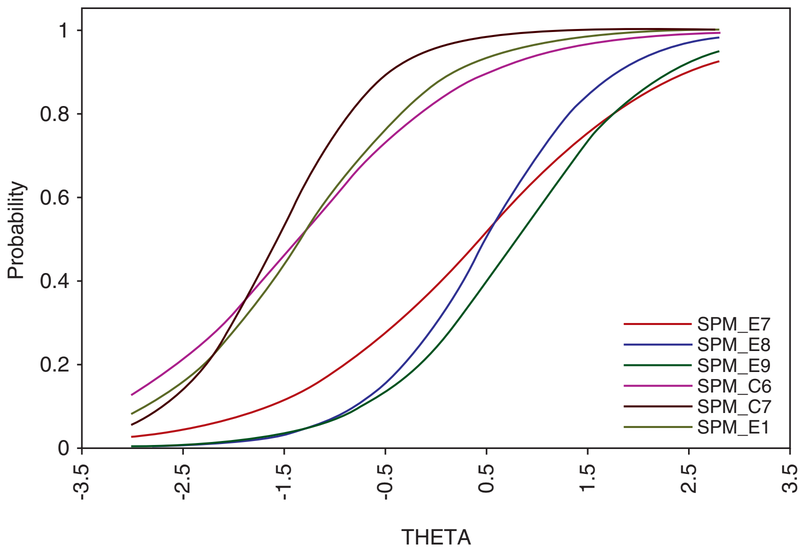


Fig. 4.3 ICC for items E9, E8, and E7 (high complexity) and items C7, C6, and E1 (low complexity) from the SPM test

value, it is not sufficient for subsequent analysis. It was necessary to achieve a perfect agreement among raters related to the type of error represented by each answer alternative of the E7 item. With a defined error type for each wrong answer alternative, it becomes possible to identify the predominant type of error made by students with high and low cognitive performance.

The disagreement among raters for item E7 was concentrated on alternatives 3 and 7. A rater classified both alternatives as Error Type II. An email was sent to this rater asking for confirmation of this classification or to indicate another possible classification. The rater responded by changing the evaluation to Error Type I (for alternative 3) and to Error Type IV (for alternative 7), which was the same evaluation made by the other raters.

After defining the type of error for all answer alternatives (items E7, E8, and E9), the samples from Argentina, Brazil, Colombia, and Peru (n = 2,454) were analyzed. Unfortunately, there was no available data from Chile and Mexico. The answers from these two countries were permanently codified as 0 (“wrong”) or 1 (“correct”). Before presenting the results, the reader must note that other raters cannot generalize the achieved classification, insofar as the raters in the present study were not randomly selected from a population of raters.

Considering the most difficult items (E7, E8, and E9) from the group of SPM items representing unidimensionality, our raters indicated:

- Five answer alternatives representative of Errors Type I (E7_3, E8_3, E8_4, E9_1, and E9_5);
- Five answer alternatives representative of Errors Type II (E7_2, E7_8, E8_9, and E9_7);
- Four answer alternatives representative of Errors Type III (E7_4, E8_7, E9_6, and E9_8); and,
- Seven wrong alternatives representative of Errors Type IV (E7_5, E7_6, E7_7, E8_1, E8_2, E9_2, and E9_4).

Tables 4.5, 4.6, and 4.7 demonstrate the type of errors for each wrong answer alternative for each item.

From the total sample, only the high (Q4; n = 538) and low performer (Q1; n = 600) groups in the SPM test, according to their score on the first dimension (based on 16 items), were analyzed.

Table 4.5 Type of error for each wrong alternative answer for item E7 of the SPM test

Wrong answer alternatives	Type	Meaning
2	II	Repetition errors
3	I	Incomplete correlate errors
4	III	Difference errors
5	IV	Wrong principle errors
6	IV	Wrong principle errors
7	IV	Wrong principle errors
8	II	Repetition errors

Table 4.6 Error type and wrong alternative answer for item E8

Wrong answer alternatives	Type	Meaning
1	IV	Wrong principle errors
2	IV	Wrong principle errors
3	I	Incomplete correlate errors
4	I	Incomplete correlate errors
5	II	Repetition errors
7	III	Difference errors
8	II	Repetition errors

Table 4.7 Error type and wrong alternative answer for item E9

Wrong answer alternatives	Type	Meaning
1	I	Incomplete correlate errors
2	IV	Wrong principle errors
4	IV	Wrong principle errors
5	I	Incomplete correlate errors
6	III	Difference errors
7	II	Repetition errors
8	III	Difference errors

For item E7, 85.8% of the low performing group (Group 1) and 26.6% of the high performing group (Group 4) responded incorrectly. Considering only wrong answers, the alternative most indicated (20.6%) by the Q1 group was alternative 6 (wrong principle error), while alternative 3 (incomplete correlate error) was the most indicated (32.9%) by the Q4 group (Fig. 4.4). As previously mentioned, incomplete correlate error indicates suboptimal information processing, while wrong principle error is a serious failure of information processing.

In the case of item E8, 93.8% of the low-performing group (Q1) and 21.6% of the high-performing group (Q4) responded incorrectly. The wrong alternatives most indicated (approximately 24%) by the Q1 group were alternatives 1 and 2 (wrong principle error), with the same alternatives most indicated (average 22%) by the Q4 group (Fig. 4.5).

In the case of item E9, 94.3% of the low performing group (Q1) and 32.7% of the high performing group (Q4) responded incorrectly. The alternative most indicated (25.1%) by the Q1 group was alternative 4 (wrong principle error), while the most commonly indicated wrong alternative (29%) by Q4 group was alternative 1 (incomplete correlate errors), shown in Fig. 4.6.

In order to visualize the most indicated type of error in each group of performers (high and low), we averaged the percentages of the alternatives and item group that represented each type of error. For example, Type I error (Incomplete correlate errors) was represented by the following alternatives: E7_3, E8_3, E8_4, E9_1, and E9_5. The percentage of students of low performance (Q1) who indicated these alternatives was 14.4, 5.2, 3.9, 14.5, and 10.8, respectively. In this case, Type I error was executed by 9.76% of students from the Q1 group (and 14% from the Q4 group). The total results are shown in Fig. 4.7.

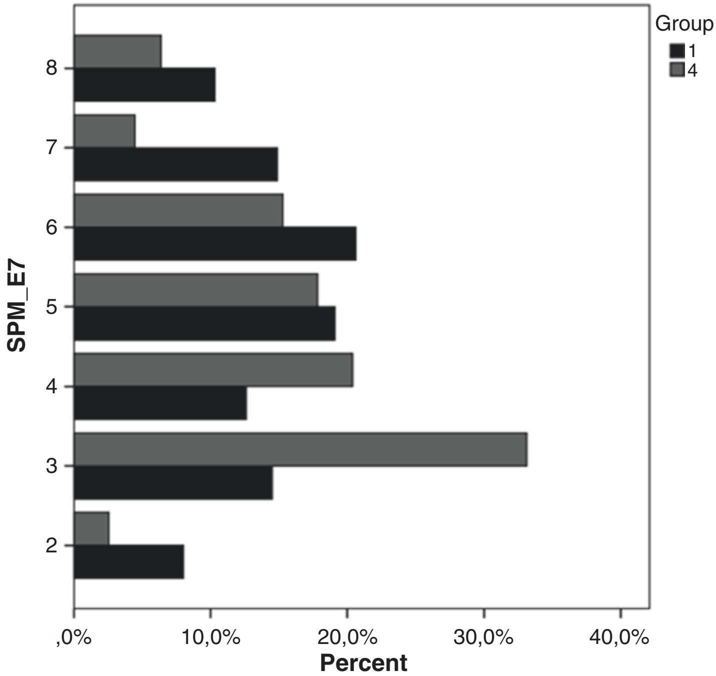


Fig. 4.4 Distribution percentage of wrong answers for each alternative made by high (Group 4; gray bar) and low performer (Group 1; black bar) groups for item E7

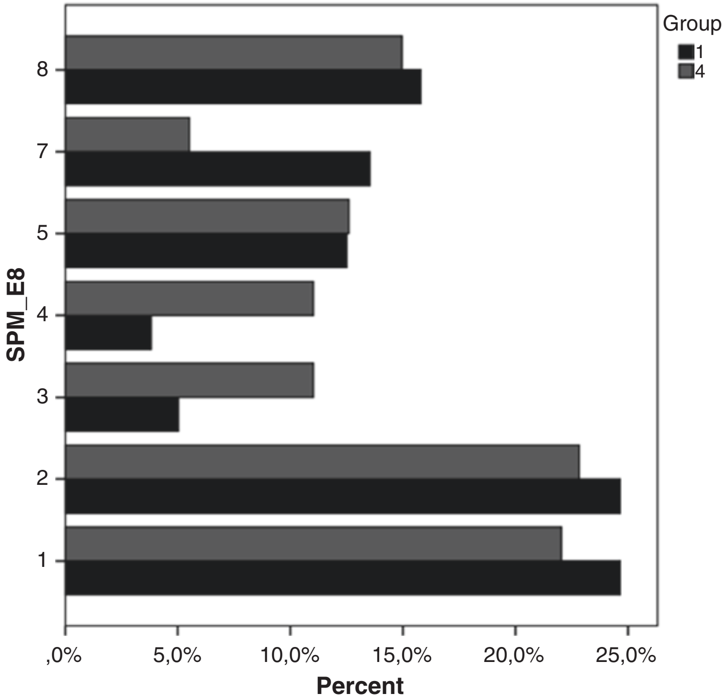


Fig. 4.5 Distribution percentage of wrong answers for each alternative made by high (Group 4; gray bar) and low performer (Group 1; black bar) groups for item E8

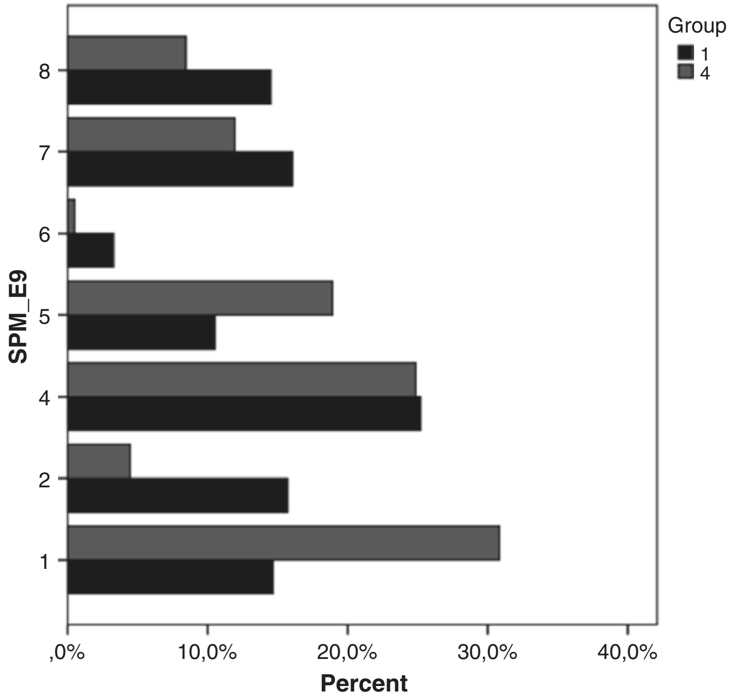


Fig. 4.6 Distribution percentage of wrong answer for each alternative made by high (Q4; gray bar) and low performer (Q1; black bar) groups for item E9

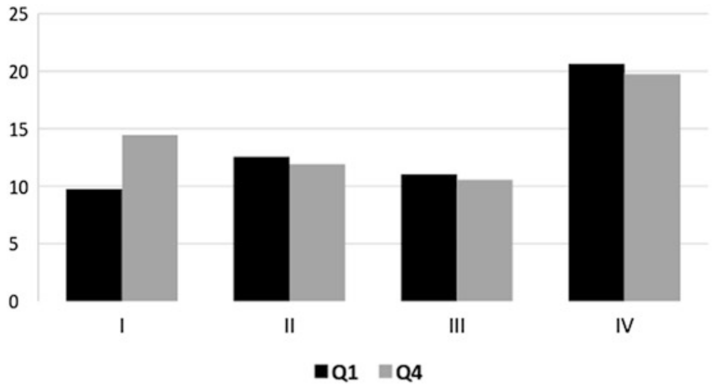


Fig. 4.7 Average percentage of wrong answer alternatives considering type of error and group of performers (Q1 and Q4). Note there is not an equal number of the error types across the SPM test or even across any given item. For this reason, the total percentage does not reach 100%

Figure 4.7 shows slight percent differences between high and low performers when they chose Type II, III, and IV errors. However, more high performers chose Type I error (incomplete correlate errors) than low performers. These results were expected, according to previous studies.

4.2 Creativity

Once during a cognitive assessment session, a child was asked: What is the similarity between kilogram ("Quilo" in Portuguese) and meters? The child replied: If you add "quilo" to the word "meter", you get kilometer. The comments among the researchers were varied, where some of them considered the answer as creative insofar as there was originality (production of a new word "kilometer"). Others considered it simply as a wrong answer to the posed question ("What is the similarity … .").

In the 1990s, Chris Ofile, a British Turner Prize-winning painter, became famous for his paintings made with elephant dung. Many people attended European and American museums to see his productions and some critics considered him a genius. However, this kind of production caused outrage for Mario Vargas Llosa, the Peruvian writer and 2010 Nobel prize-winner, and he wrote a column about it ("Caca de Elefante") in the Spanish Journal *El Pais* (https://elpais.com/diario/1997/09/21/opinion/874792810_850215.html). According to Llosa, modern art would not have esthetic sensibility or any criteria to evaluate good taste. Was the child's answer and Chris Ofile's art both expressions of creativity? According to the Cambridge dictionary, creativity is the ability to produce novelty and original ideas, or elaborate something new and imaginative. However, what is "novelty," "original," "new," or "imaginative"? Therefore, creativity is a concept that is difficult to define and assess (Butcher, 1968; Ludwing, 1995).

Scientifically, at the end of the first half of the last century, psychology researchers showed interest in creativity after the American psychometrician Joy Paul Guilford addressed this subject in his speech as President of the American Psychological Association (Guilford, 1950). In this address, Guilford reported that only 186 article titles out of 121,000 (0.15%) had been indexed on the subject of creativity in the Psychological Abstract[1] since its origin. Guilford argued against the notion that creativity would be expected only in individuals with a high IQ. He considered creativity as an ability (or trait). Creativity would present continuity and, therefore, like any ability, creativity would present normal distribution (normal variability) in the population. Thus, creativity could be measured through psychological tests. However, he recognized the impossibility of measuring creativity using the traditional format of ability tests.

[1] Psychological Abstract, a world-class resource for abstracts, was replaced in 2006 by the database named PsycINFO.

According to Guilford, scoring based on absolute answers would be contrary to the notion of novelty creation. Guilford sketched his first ideas on a concept that became famous in the literature in relation to creativity, which was described as "divergent thinking," the ability to give multiple, novel ideas and creative answers/solutions to open and less structured questions. Convergent thinking would be the opposite to creative thinking, described as the ability to give the correct answer to problems/questions that require a standard solution. Some tasks for assessing creativity were mentioned by Guilford, for example, producing questions based on material previously seen. Those questions could include but are not limited to naming common household appliances (e.g., toaster, articles of clothing) and things that could be improved. Alternatively, general instruction, such as "do something with each item; whatever you think should be done." Guilford was conscious of the low or moderate correlation between intelligence performance and creativity, and at this point, he predicted that the explanation for the almost absent correlation could be in the field of non-cognitive traits.

In the 1960s, Guilford (1967) developed a model of creativity based on three components: sensitivity to problems (recognition of problems), fluency (ability to generate a number of answers), and flexibility (transformation of answers or knowledge in novel and high-quality responses/information). His studies suggested that certain threshold levels of IQ (most likely an IQ of 120) would be necessary for high creativity. This kind of result was later known as "The Threshold Hypothesis." Considerable research and psychometric measures were produced following Guilford's model. Perhaps the most well-known worldwide test for creativity is the Torrance Test of Creative Thinking, which was originally composed of four scales: fluency (total number of relevant ideas), flexibility (number of different categories of relevant responses), originality (statistical rarity in answer/responses), and elaboration (amount of detail in the responses). Based on his own research, Torrance considered creativity and intelligence as independent psychological constructs (Torrance, 1972). However, recent literature has presented the opposite, i.e., a consistent relationship between intelligence and creativity (Benedek, Jauk, Sommer, Arendasy, & Neubauer, 2014; Jauk, Benedek, Dunst, & Neubauer, 2013; Kim, 2005; Nusbaum & Silvia, 2011).

The expression of creativity has been classified in several ways. For example, Eysenck (1995) divided creativity into creative potential (ability to create novel and unique ideas or things admired by a noteworthy audience), and creative achievement (production, real-life accomplishment as scientific discoveries, novel writing, arts, etc.). Simonton (1994, 2004) proposed "Big-C" and Richards (1993, 2007) proposed "little-c" to characterize eminent creative contributions (Big-C) and creative actions on everyday activities (little-c), respectively. Kaufman and Beghetto (2009) proposed a gradation between Big-C and little-c, and presented a model of creativity of four dimensions: mini-c (e.g., inspiration, insights), little-c (playing a new song on the piano, acting in a domestic production), Pro-c (e.g., change of job, engagement in a political movement), and Big-C (e.g., medals, social achievements recognition).

Independent of the creativity classification, the biggest challenge to Differential Psychology in the field of creativity is related to the Threshold Hypothesis (TH). This hypothesis assumes a stronger relationship between creativity and intelligence in groups of individuals with a low IQ, while a low (or nil) correlation is found in groups with a high IQ. In other words, until a certain level of intelligence, creativity is part of the cognitive system. At higher levels of intelligence, creativity acts as an independent ability. Some researchers (Cho, Nijenhuis, van Vianen, Kim, & Lee, 2010; Jauk et al., 2013) have found a curvilinear relationship between creativity and intelligence (TH was supported), while others (Preckel, Holling, & Wiesse, 2006) found a linear relationship (TH was not supported). Moreover, some researchers (Karwowski et al., 2016) have found mixed results (TH was partially supported).

In order to verify the existence of TH in Latin American data, we analyzed the performance in the CV1 (verbal) and the CF2 (figurative) of 1225 students from Brazil, Colombia, Peru, and Mexico. Unfortunately, samples from Argentina and Chile were not submitted to these specific tests. CV1 and CF2 could be considered as measures of potential creativity (ability to produce new responses), not as creative achievement measures (real-life outcomes as result of the potential creativity).

Pearson bivariate correlations were conducted between creativity performance (verbal and figurative) and variables, such as intelligence (SPM), sex, and school SES. Significant correlations were observed between CV1 (verbal) and sex ($r = .100$, $p = .001$), and school SES ($r = .166$, $p = .000$). The SPM test was not significantly associated with CV1. Regarding CF2 (figurative), there was significant association with the SPM test ($r = .083$, $p = .004$) and school SES ($r = .147$; $p = .000$), but not with sex.

The next step was to use the metric scale of IQ using a conversion of the SPM raw score and divide the sample into a high group (IQ $\geq$ 120) and a middle-low-performance group (IQ $\leq$ 120). The aim was to verify if the correlation between intelligence and creativity could be affected by levels of intelligence.

Table 4.8 indicated significant association between intelligence and creativity (verbal and figurative) for the group with low cognitive ability. Regarding the group with high cognitive performance, significant but negative association was found with verbal creativity.

In order to model the relationship between the explanatory variables (SPM score, sex, school SES) and the predicted variable (creativity), a multiple linear regression was calculated for each group (high and low performance). In the case of CV1, a significant regression equation was measured [$F(3, 1083) = 13.074$, $p = .000$; R^2 of

Table 4.8 Correlation between creativity and intelligence

Creativity measures	SPM Middle-low performance ($n = 1087$)	High performance ($n = 138$)
Verbal Creativity (CV1)	.070*	.080
Figurative Creativity (CF2)	.083**	.015

*Correlation significant at the .05 level

**Correlation significant at the .01 level

.035] for the middle-low-performance group (IQ ≤ 120). Specifically, school SES (β = .148, p = .000), and sex (β = .087, p .004) were significant predictors of CV1. The SPM performance was not a significant predictor. For the high-performance group (IQ ≥ 120), a significant regression equation was found [F(3, 134) = 3.551, p = .016], and R^2 of .074. School SES (β = .229, p = .007) was the only significant predictor of CV1.

In the case of figurative creativity (CF2), a significant regression equation was found in the low-performance group [F(3, 1083) = 9.332, p =.000], and R^2 of .025. The school SES (β = .140, p = .000) was the only significant predictor. For the high-performance group, there were no significant predictors.

In short, a significant relationship between intelligence and creativity was found in middle-low cognitive group (instead of the high cognitive group), which means that creativity is part of intelligence until a certain level of cognitive performance (IQ above 120). However, multiple linear regression indicated that the effect of intelligence on creativity disappeared when school SES entered on the model.

4.3 Conclusion

The PISA test is not just a school performance test that depends exclusively on the level of school knowledge; it is also an excellent individual problem solving test.[2] Our data indicated that, as expected, more students with high cognitive ability (36.4%) than students with low cognitive ability (8.7%) solved the four most difficult problems presented in the short version of the PISA test. This tendency (better problem solving in the high cognitive group) was more noticeable in the Brazilian (50% on average) and Argentine (44.4%) samples than in the Colombian sample (14.6%). This kind of result is robust enough to be considered by the Organisation for Economic Co-operation and Development (OECD) when it looks for the factors that influence educational outcomes. Intelligence (or *g* factor, or psychometric intelligence) is a special contributor for individual differences in solving problems. However, another factor is the quality of the school environment and this deserves attention from education policy makers. In our study, students with high intelligence but enrolled in schools of low SES solved difficult problems at a lower rate (13%) compared to students with the same intelligence level but enrolled in schools of high SES (45.5%). This phenomenon is reminiscent of the spillover effect, i.e., the spreading of something or situation on somewhere else with the same effect. James Flynn has used the term spillover for explaining how IQ of individuals (social multipliers) affect their communities and vice versa. He wrote:

> "Therefore, unless you are part of a very isolated group, whether you live in a high- or low-IQ community should affect your IQ. Moreover, if there is a cognitively elite group in your

[2] Since 2015, there is a new version of the PISA test that measures collaborative problem solving skills.

city or town, their high IQ should have effects that spill over to the whole community" (Flynn, 2007; p. 94).

However, in our case, differences in the school environment clearly affected the school performance of groups with the same cognitive level. Regarding potential creativity, our study supported previous studies that showed a significant relationship (but very small) with intelligence only in groups with a low intelligence level. However, when variables such as sex and school SES were inserted into the model, school SES was the most important predictor, at least for Latin American students.

References

Anderson, J.R. (1990). *Cognitive psychology and its implications* (3rd ed.). New York: W.H. Freeman and Company.

Babcock, R. L. (2002). Analysis of age differences in types of errors on the Raven's advanced progressive matrices. *Intelligence, 30*, 485–503.

Benedek, M., Jauk, E., Sommer, M., Arendasy, M., & Neubauer, A. C. (2014). Intelligence, creativity, and cognitive control: The common and differential involvement of executive functions in intelligence and creativity. *Intelligence, 46*, 73–83. https://doi.org/10.1016/j.intell.2014.05.007

Butcher, H. J. (1968). *Human intelligence—Its nature and assessment*. London: Methuen.

Cho, S. H., Nijenhuis, J. T., van Vianen, A. E. M., Kim, H., & Lee, K. H. (2010). The relation between diverse components of intelligence and creativity. *Journal of Creative Behaviour, 44*, 125–137.

Chuderski, A. (2015). Why people fail on the fluid intelligence tests. *Journal of Individual Differences, 36*(3), 138–149. http://psycnet.apa.org/doi/10.1027/1614-0001/a000164

Eysenck, H. (1995). *Genius: The natural history of creativity*. New York: Cambridge University Press.

Flynn, J. (2007). *What is Intelligence?: Beyond the Flynn effect*. London: Cambridge University Press.

Greeno, J. G., & Simon, H. A. (1988). Problem solving and reasoning. In R. C. Atkinson, R. J. Herrnstein, G. Lindzey, & R. D. Luce (Eds.), *Stevens' handbook of experimental psychology, Learning and cognition* (Vol. 2, 2nd ed., pp. 589–672). New York: Wiley.

Guilford, J. P. (1950). Creativity. *The American Psychologist, 5*, 444–454.

Guilford, J. P. (1967). *The nature of human intelligence*. New York: McGraw-Hill.

Gunn, D., & Jarrold, C. (2004). Raven's matrices performance in Down syndrome: Evidence of unusual errors. *Research in Developmental Disabilities, 25*, 443–457.

Hunt, E. B. (1989). Cognitive science: definition, status, and questions. *Annual Review of Psychology, 40*, 603–629.

Jauk, E., Benedek, M., Dunst, B., & Neubauer, A. C. (2013). The relationship between intelligence and creativity: New support for the threshold hypothesis by menos of empirical breakpoint detection. *Intelligence, 41*, 212–221. https://doi.org/10.1016/j.intell.2013.03.003

Karwowski, M., Dul, J., Gralewski, J., Jauk, E., Jankowska, D. M., Gadja, A., … Benedek, M. (2016). Is creatitivity without intelligence possible? A necessary condition analysis. *Intelligence, 57*, 105–117.

Kaufman, J. C., & Beghetto, R. A. (2009). Beyond big and little: The four C model of creativity. *Review of General Psychology, 13*, 1–12.

Kim, K. H. (2005). Can only intelligent people be creative? *Journal of Secondary Gifted Education, 16*, 57–66.

Kunda, M., Soulières, I., Rozga, A. & Goel, A.K. (2013). *Methods for classifying errors on the Raven's standard progressive matrices test*. Proceedings of the Annual Meeting of the

Cognitive Science Society (COGSCI'13), pp. 2796–2801 Retrieved from https://pdfs.semanticscholar.org/a78a/8ab8b0b887a59d03bae2ff83b9079794ee93.pdf.

Kunda, M., Soulieres, I., Rozga, A., & Goel, A. (2016). Error patterns on the Raven's standard progressive matrices test. *Intelligence, 59*, 181–198.

Ludwing, A. M. (1995). What "Explaining creativity" doesn't explain. *Creativity Research Journal, 8*, 413–416.

Mackintosh, N. J., & Bennett, E. S. (2005). What do Raven's matrices measure? An analysis in terms of sex differences. *Intelligence, 33*, 663–674. https://doi.org/10.1016/j.intell.2005.03.004

Nusbaum, E. C., & Silvia, P. J. (2011). Are intelligence and creativity really so different? Fluid intelligence, executive processes, and strategy use in divergent thinking. *Intelligence, 39*, 36–45.

Preckel, F., Holling, H., & Wiesse, M. (2006). Relationship of intelligence and creativity in gifted and non-gifted students: An investigation of threshold theory. *Personality and Individual Differences, 40*, 159–170.

Raven, J., Raven, J. C., & Court, J. H. (2000). *Manual for Raven's progressive matrices and vocabulary scales. Section 3: The standard progressive matrices*. Oxford, England: Oxford Psychologists Press.

Richards, R. (1993). Everyday creativity, eminent creativity, and psychopathology. *Psychological Inquiry, 4*, 212–217.

Richards, R. (2007). Everyday creativity: Our hidden potential. In R. Richards (Ed.), *Everyday creativity and new views of human nature* (pp. 25–45). Washington, DC: American Psychological Association.

Simonton, D. K. (1994). *Greatness: Who makes history and why*. New York: Guilford Press.

Simonton, D. K. (2004). *Creativity in science: Chance, logic, genius, and zeitgeist*. Cambridge, UK: Cambridge University Press.

Stadler, M., Becker, N., Godker, M., Leutner, D., & Greiff, S. (2015). Complex problem solving and intelligence: A meta-analysis. *Intelligence, 53*, 92–101.

Torrance, E. P. (1972). Can we teach children to think creatively? *Journal of Creative Behaviour, 6*, 114–143.

Van Herwegen, J., Farran, E., & Annaz, D. (2011). Item and error analysis on Raven's CPM in Williams syndrome. *Research in Developmental Disabilities, 32*, 93–99.

Vernon, P., & Strudensky, S. (1988). Relationship between problem-solving and intelligence. *Intelligence, 12*, 435–453.

Vodegel Matzen, L. B. L., Van der Molen, M. W., & Dudink, A. C. M. (1994). Error analysis of Raven test performance. *Personality and Individual Differences, 16*, 433–445. https://doi.org/10.1016/0191-8869(94)90070-1

Vosniadou, S. (1988). *Analogical reasoning as a mechanism in knowledge acquisition: A developmental perspective.* Center for the Study of Reading. Technical Report, n. 438. University of Illinois. Retrieved from https://www.ideals.illinois.edu/bitstream/handle/2142/18000/ctrstreadtechrepv01988i00438_opt.pdf?sequence=1.

Wustenberg, S., Greiff, S., & Funke, J. (2012). Complex problem solving—More than reasoning? *Intelligence, 40*, 1–14.

Chapter 5
Cognitive Sex Differences

Abstract The area of sex differences is one of the most controversial subjects in social sciences, especially when significant differences are detected in the field of intelligence. In this chapter, we offer results from several studies conducted at specific and general levels of intelligence using a variety of different cognitive measures. Finally, we present results obtained from our SLATINT Project.

Cognitive sex differences are a sensitive area. Two well-known events involving renowned academics exemplify this sensitive subject. The first example comes from Lawrence Summers, the American economist and 27th president of Harvard University (2001–2006), who was compelled to resign from his position after his speech about women's representation in science. In a conference on diversity, Summers hypothesized that when looking deeper into the differences of intrinsic aptitudes, especially in mathematic abilities, there would be sex differences in the standard deviation (less females than males at the top and bottom of the distribution). Helmut Nyborg, a Danish psychologist, is our second example. In the peer-reviewed journal *Personality and Individual Differences*, Nyborg published an analysis based on data from 62 Danish adults. He concluded that cognitive sex differences, equivalent to 8.55 IQ points, were genuine and were favorable to males (Nyborg, 2005). The Danish society and part of his academic staff did not agree with Nyborg's conclusion and Nyborg was temporarily suspended from his position as professor.

Both examples indicate that conducting a scientific study on cognitive sex differences can be a risky endeavor. Effectively, it is difficult to imagine a researcher writing a grant proposal aimed at studying sex differences in intelligence, or receiving funds from major research funding agencies for this subject matter. Most opposition comes from the fear of reinforcing misogyny, if significant differences favoring males were to be detected in such research. In this regard, we agree with the words of the American psychologist Diane Helper, 2014 President of the American Psychological Association, whose scientific production is considered the gold standard in cognitive sex differences:

C. Flores-Mendoza et al., *Intelligence Measurement and School Performance in Latin America*, https://doi.org/10.1007/978-3-319-89975-6_5

> "Despite legitimate concerns about the misuse of data, the only alternative to sex differences research is pretending that differences do not exist, which will not advance understanding or reduce prejudice. Ignorance is not an antidote for prejudice …" (Halpern, 2011, p.5).

How much knowledge have we accumulated through the investigation of cognitive gender differences? There is considerable knowledge but no certainty. Some studies have not found cognitive sex differences (Colom, García, Juan-Espinosa, & Abad, 2002; Colom & García-Lopez, 2002; Colom, Juan-Espinosa, Abad, & García, 2000; Van der Sluis et al., 2006), while samples of males outperforming females (Irwing, 2012; Jackson & Rushton, 2006; Lynn & Irwing, 2004), especially in tests that demand fluid intelligence, were also found.

According to Jensen (1998, p. 536–537), when two groups are compared in cognitive tests, such as males and females, "there is an incomprehensible torrent of different results." Several factors, such as the influence of hormones (Guerrieri et al., 2016), gender-stereotyping (Hirnstein, Coloma Andrews, & Hausmann, 2014), brain anatomy (Giedd, Raznahan, Mills, & Lonroot, 2012), or number and distribution of neocortical neurons (Stark et al., 2007) have been indicated as being explanatory of such a diversity of results. However, there is no research regarding cognitive sex differences in regions outside the EUA-Europe axis. In this chapter, we analyze cognitive sex differences on Latin American samples based on three known psychological factors (cognitive distribution variability, differences in sexual development, and specificity/generality of tasks).

5.1 Variability Hypothesis

The variability hypothesis is the difference between males and females in the distribution of intelligence scores. The same hypothesis was raised by Lawrence Summers, as mentioned previously. This hypothesis was presented and greatly debated at the beginning of the last century (e.g., Leta Hoollingworth, Lewis Terman and Catherine Miles) when greater cognitive male variability (more males at both extremes of the ability spectrum) than female variability was found. The over-representation of males at the bottom and at the top ends of the distribution would suggest why more males than females are found in mental handicap institutions or in jobs related to Science, Technology, Engineering, or Mathematics (STEM). Some studies have supported this hypothesis (Caplan, Crawford, Hyde, & Richardson, 1997; Dykiert, Gale, & Deary, 2009; Machin & Pekkarinen, 2008) while others reject it (Feingold, 1994). Using a large dataset from the Scottish Mental Survey (1932 and 1947), Johnson, Carothers, and Deary (2008) found partial support for the variability hypothesis. However, they proposed a novel explanation, i.e., that general intelligence could be conceptualized from two distributions. One of these distributions describes genetic and environmental syndromal conditions that may disrupt general intelligence (here, males are more represented). The second distribution reflects performance, without such disruption (here, females are more represented).

5.1.1 *The Variability Hypothesis in Latin American Studies*

Previous testing of the variability hypothesis in Latin America is almost non-existent. Thus, we analyzed the same sample used in a paper published in 2013 (Flores-Mendoza et al., 2013) for information regarding the variable hypothesis in Latin America. This study refers to a Brazilian sample (n = 2064), 55% females, aged between 13 and 58 years (45% over 18 years). The participants were recruited from high schools, universities, university preparatory courses, and human resources focusing on education-related jobs, thus all participants were involved in educational fields, which explains the female predominance. The majority of participants were from the state of São Paulo (n = 1455), the normative sample of the cognitive measure (BPR5) used in this study; but individuals from the state of Minas Gerais (n = 609) were also included. Both Brazilian states constitute the strongest commercial and industrial markets in Brazil (first and third highest GDP, respectively). The Brazilian Cognitive Reasoning Battery [BPR5] (Almeida & Primi, 1998) consists of five reasoning tests: verbal reasoning (VR), numeric reasoning (NR), spatial reasoning (SR), mechanical reasoning (MR), and abstract reasoning (AR). The VR takes 10 minutes, NR and SR 18 minutes each, MR 15 minutes, and AR 12 minutes. Thus, complete administration of the BPR5 takes 73 minutes. The B form (people with at least high school education) was analyzed in this study. Item information was available in the sample taken from Minas Gerais. The alpha coefficients obtained were .83 for VR; .85 for AR; .78 for MR; .82 for SR, and .89 for NR.

Table 5.1 shows descriptive statistics for females and males, based on the BPR5. We observed negative skewness and kurtosis data for males and females. While kurtosis did not differ significantly from the normal distribution for either males (−.249/.161) or females (−.177/.145), skewness departed from symmetry for both males (−.474/.081) and females (−.334/.072). In order to verify how our data departed from the normal distribution, we calculated the effect size from D'Agostino's K-squared test of normality [DK = skewness $(\text{Stat/SE})^2$ + kurtosis $(\text{Stat/SE})^2$ follows X^2 with df = 2]. The effect size is calculated by dividing the X^2 of DK by the total number of cases. In the case of female data, the effect size was 0.02, which means a weak effect, i.e., the distribution did not differ much from the normal distribution. When analyzing male data, the effect size was 0.04, i.e., the asymmetry in males was higher than in females, but the distributions did not differ much from normal distributions.

The variability hypothesis (Dykiert et al., 2009) was investigated by transforming the raw total score of BPR5 to the z score and then to an IQ metric with a mean

Table 5.1 Descriptive statistics and mean differences of each subtest of the BPR5

									Skewness		Kurtosis	
Sex	*N*	Mean	SD	Min	Q1	Q2	Q3	Max	Stat	SE	Stat	SE
Female	1144	62.5	17.9	6	51	63	76	104	−.334	.072	−.177	.145
Male	920	70.9	18.4	15	59	72	85	105	−.474	.081	−.249	.161
Total	2064	66.3	18.6	6	54	67	80	105	−.350	.054	−.265	.108

Note: *SD* = Standard Deviation, *Min* = Minimum, *Q1* = Quartile 1, *Q2* = Quartile 2, *Q3* = Quartile 3, *Max* = Maximum, *Stat* = Statistic, *SE* = Standard Error of 100 and standard deviation of 15. In contrast to other studies that usually use a brief or quick cognitive measure, our study referred to the cognitive performance assessed by five different tests over a longer duration and fixed assessment time (1 hour and 13 minutes).

Figure 5.1 shows the IQ distribution of males and females. Due to the lower frequency of males in our sample, we consider the percentage of females and males along the IQ scale. For the IQ range 60–85, we found a male:female rate of 0.5:1; for the IQ range 90–110 the rate was 0.9:1 and for the range 115–135 the rate was 2.6:1. Thus, there was a higher concentration of males in the higher IQ levels.

However, in the study of Flores-Mendoza et al. (2013), a large sex difference in the Reasoning Mechanical (RM) test of the BPR5 was detected. Thus, we performed the same estimation as previously conducted but without RM. Figure 5.2 shows the new distribution for males and females. This time, the male:female ratio for the IQ range of 60–85 was 0.96:1; for the IQ range of 90–110 and for the IQ 115–135 the ratio was 1:1. Therefore, differences in the male:female ratio in each IQ range effectively disappeared.

Another study (Flores-Mendoza, Darley, & Fernandes, 2016) showed Brazilian sex differences in a large sample of university students (n = 1042), 63% females, aged between 17 and 60 years (mean = 22.3; SD = 4.6), assessed with the Advances Progressive Matrices (APM). The percentage of males and females in each quartile of the distribution of the APM score was presented, which is useful for inferring information about sex variability. Similar to the BPR5, there were significant differences between males and females at the lowest quartile (Q1) (z = −4.084; one-tail

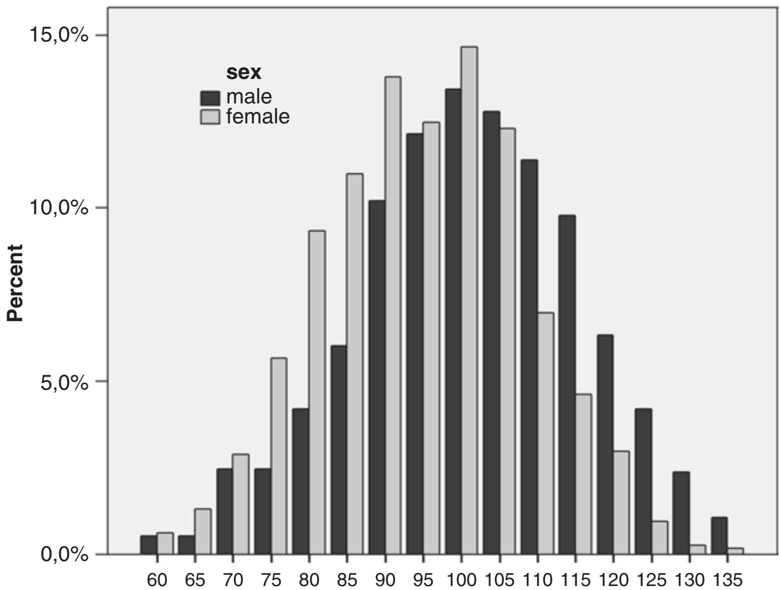


Fig. 5.1 Percentage of males and females along the IQ scale based on the BPR5

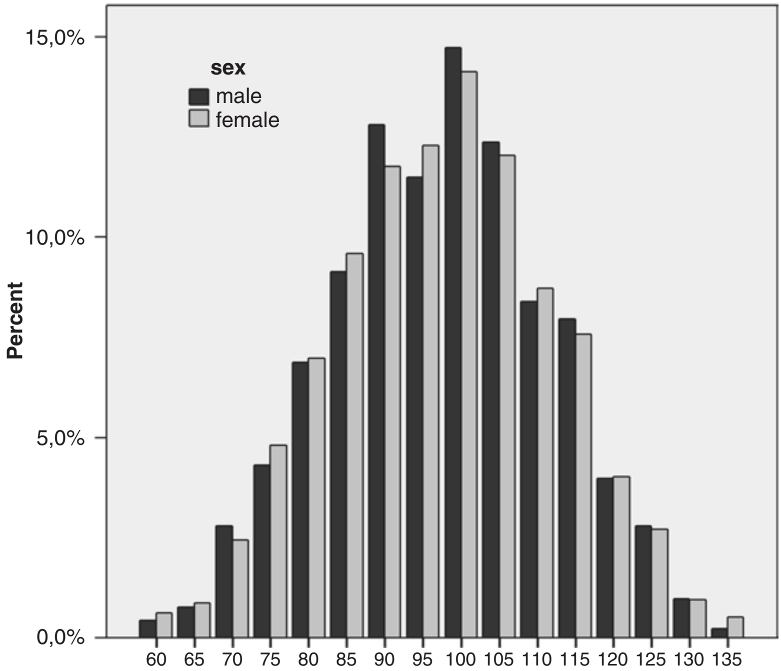


Fig. 5.2 Percentage of males and females along the IQ scale based on the BPR5 (without mechanical reasoning)

probability < .001), i.e., there was a higher proportion of women at Q1. On the other hand, the difference in proportions at the highest quartile (Q4) was $z = -4.49$; one-tail probability < .001, indicating a higher proportion of males at Q4 on the APM test (Fig. 5.3).

5.1.2 Testing the Variability Hypothesis with the Sample from the SLATINT Project

The cognitive measure most often administered in the SLATINT Project was the SPM test (n = 3805 including samples from Argentina, Brazil, Chile, Colombia, Mexico, and Peru). Coincidently, the SPM test is the most commonly used test in previous studies investigating the variability hypothesis. For this reason, the SPM was chosen for analyzing the variability hypothesis. Table 5.2 indicates that the distribution of the SPM scores in our sample largely departed from a normal distribution. For both females and males, the skewness was negative and kurtosis was positive. D'Agostino's K-squared test of normality indicated an effect size of 0.565 for female distribution, which means a strong effect, i.e., the distribution differed

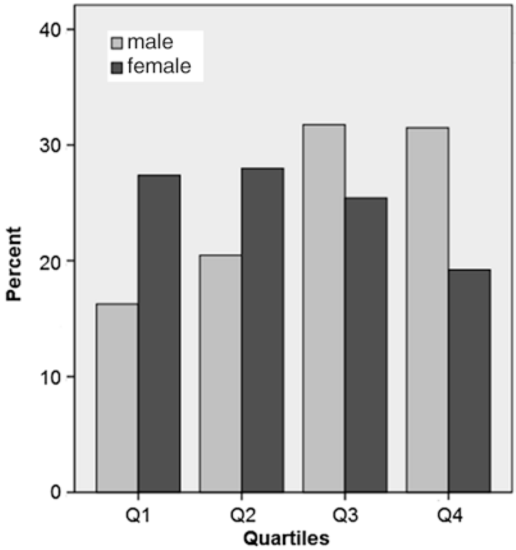


Fig. 5.3 Percentage distribution of APM scores according to quartiles for each sex (reproduced from the study conducted by Flores-Mendoza et al., 2016; with permission of Mankind Quarterly)

Table 5.2 Descriptive statistics and mean differences of the SPM test for the sample from the SLATINT Project

Sex	*N*	Mean	SD	Min	Q1	Q2	Q3	Max	Skewness		Kurtosis	
									Stat	SE	Stat	SE
Female	1938	44.5	7.8	7	40	46	50	60	−1.27	0.06	2.80	0.11
Male	1867	45.2	8.0	6	41	46	51	60	−1.30	.006	2.92	0.11
Total	3805	44.9	7.9	6	41	46	50	60	−1.28	0.04	2.84	0.79

greatly from the normal distribution. Similarly, there was a strong effect size for male distribution (0.628).

The non-normality of the SPM score distribution was in part due to the concentration of scores skewing towards the right side of the curve (Fig. 5.4), meaning that current Latin American adolescents easily solve the SPM test. The long left tail indicates the high variability present in our sample, which is unsurprising. Developing countries tend to have higher variability than developed countries.

Transforming the SPM raw scores into a metric scale of IQ, we found a male:female ratio of 0.95:1 for the IQ range of 60–85; for the IQ range 90–110 the ratio was 0.96:1 and for the range 115–135 the rate was 0.99:1. Thus, there was no higher male concentration in lower or higher IQ levels when the SPM test was used in Latin American samples (Fig. 5.5).

Both studies (Flores-Mendoza et al., 2013, 2016) produced results that partially corroborate the variability hypothesis for sex differences. Effectively, males are over-represented at the higher extreme of the distribution, but when mechanical reasoning was eliminated from the BPR5, no sex difference at the high end of the distribution was found. Therefore, it is possible to infer that sex differences could be

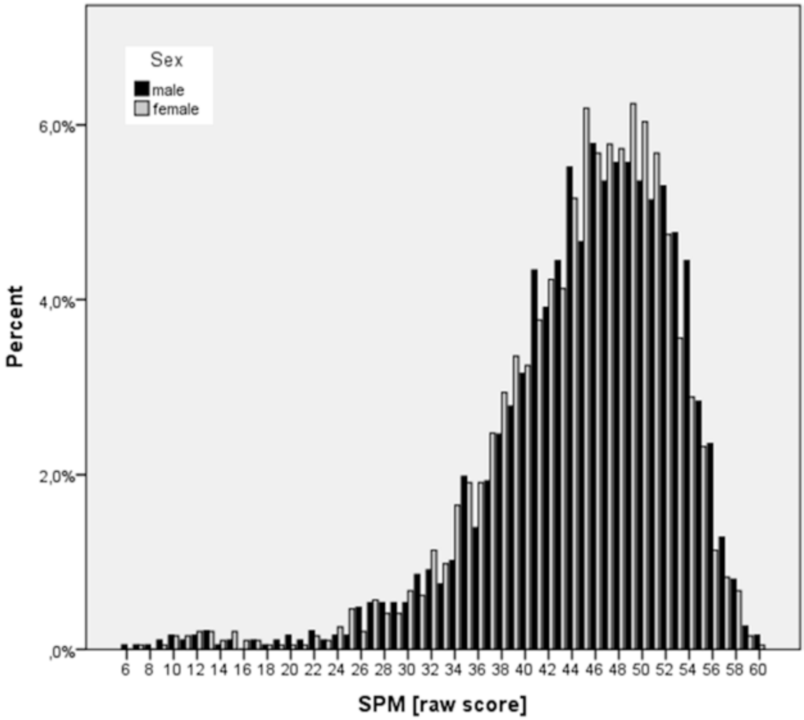


Fig. 5.4 Percentage of males and females distributed along the raw score of the SPM test of the SLATINT Project

due to effectiveness in specific abilities. On the other hand, the analysis of the SPM scores in a large Latin American sample did not support the variability hypothesis, perhaps due to lower complexity of the SPM for the current generation of students.

5.2 Developmental Theory of Sex Differences

The English psychologist Richard Lynn proposed a theory for explaining sex differences in intelligence (Lynn, 1999). From 9 to 14 years of age, there is an accelerated growth rate in girls; however, at 15 years of age and beyond, this female growth starts to slow down while boys continue growing. This general developmental principle also applies to the development of cognitive abilities. No cognitive sex differences are expected up to 9 years of age, insofar that at this period girls and boys develop in the same way. Afterwards, differences favoring females appear until 13 or 14 years of age, and from then, differences favor males. Several studies support this theory (Colom & Lynn, 2004; Lynn, 1999, 2002; Lynn & Irwing, 2004; Lynn,

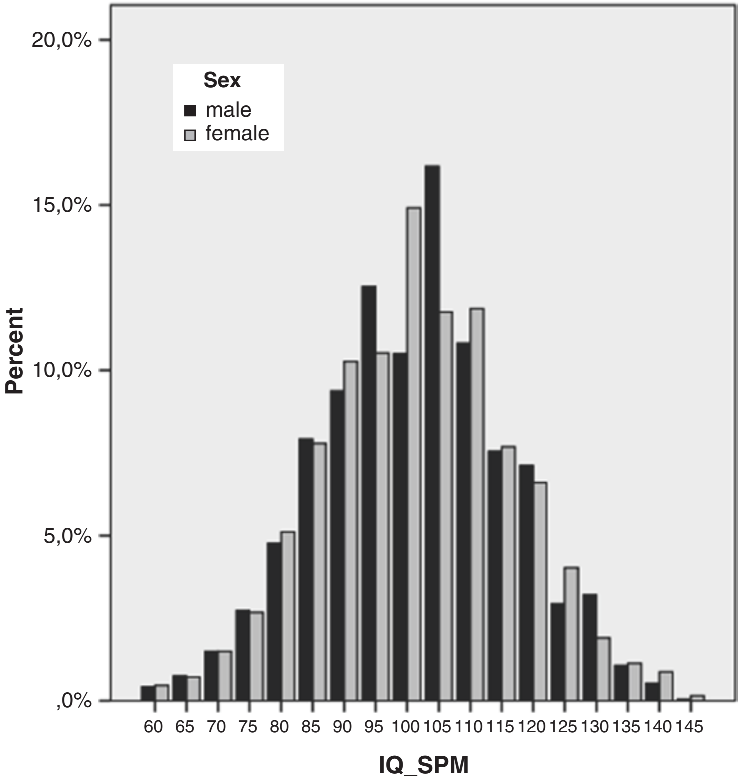


Fig. 5.5 Percentage of males and females along the IQ scale based on the SPM test of the SLATINT Project

2002; Lynn, Allik, Pullmann, & Laidra, 2004; Lynn, Backhoff, & Contreras-Niño, 2004; Lynn, Fergusson, & Horwood, 2005).

Lynn and Irwing (2004) performed a meta-analysis with 57 studies conducted in developed and developing countries. Having the Matrices Progressive of Raven as the cognitive measure in these studies, the results revealed no sex differences in children aged between 6 and 14 years; however, boys had a higher score starting at 15 years of age. In the adult population, there was a difference of 5 IQ points, favoring males. In developing countries, boys had higher mean IQs at 9 and 10 years of age. Afterwards, girls had higher mean IQs. However, at 14 years of age, boys had a higher mean IQ.

Recent studies have indicated similar results. Abdel-Khalek and Lynn (2006) showed data from children and young people assessed by the Matrices Progressives of Raven in Saudi Arabia ($n = 4659$). The results indicated higher male performance from 8 to 19 years old. However, in the group of 20- to 24-year-olds, females had higher scores. Similarly, Hur, Nijenhuis, and Jeong (2017) found in a large Nigerian sample ($n = 11{,}164$) of young people (8–19 years old), an increasing sex difference from a d of −0.006 (favoring females) to a d of 0.46 (favoring males), using the

Standard Progressive Matrices Plus (SPM+). In an Egyptian sample ($n = 722$), aged between 10 and 18 years, and assessed with the SPM test, Abdel-Khalek and Lynn (2006) found significant sex differences favoring males at the ages of 16–18 years.

The developmental theory of sex differences in intelligence was also tested in Brazil (Flores-Mendoza, Mansur-Alves, Lele, & Bandeira, 2007). Two large samples from the city of Belo Horizonte ($n = 1316$) and from the city of Porto Alegre ($n = 779$), aged between 5 and 11 years, were assessed with the CPM test (or Colored Progressive Matrices of Raven). In addition to the CPM, the sample from the Belo Horizonte city answered the Verbal Scale of WISCIII, the R-2 (a non-verbal test), Bender (psychomotor test), the Human Figure Drawing test, and the TDE (a school achievement test). Results indicated only significant mean differences (favoring females) in the Bender and the Human Figure Drawing test in 5- to 7-year-olds, and differences in writing (favoring females) at 11–12 years old. Using the Method Correlated Vectors, which is a method for analyzing group differences in general intelligence proposed by Jensen (1998), no sex differences were found.

In another large study, Flores-Mendoza, Widaman, Bacelar, and Lelé (2014) analyzed 1956 Brazilian individuals, aged between 7 and 65 years, 52.2% females, who were assessed with the Standard Progressives Matrices of Raven. In order to test the developmental effect, the authors divided the sample into two groups: 7–13 years old and 14–65 years old. The results indicated differences that favored females in the first group and favored males in the second group; however, these differences were only significant in the first group.

In general, the Brazilian studies supported the international data on the existence of cognitive sex differences, favoring females, at least in the childhood period.

5.3 Sex Differences in Specific Abilities

The evidence (including some meta-analyses) points to the fact that females, on average, have better performance in tasks that require semantic and phonologic information, perceptual speed, and verbal memory. Males have better performance in tasks that require mathematic reasoning, spatial orientation, and viso-spatial rotation (Codorniu-Roga & Vigil-Colet, 2003; Halpern, 1997; Halpern et al., 2007; Hyde, 2005; Hyde, Fennema, & Lamon, 1990; Hyde & Linn, 1988; Lubinsk, 2004; Lynn, Raine, Venables, Mednick, & Irwing, 2005; Spelke, 2005).

Sex differences in specific abilities tested in Latin American samples analyzed from univariate and multivariate statistics are now presented.

5.3.1 Latin American Sex Differences in Univariate Analysis

There are only a few Latin American studies designed to verify cognitive sex differences (Flores-Mendoza et al., 2013). From these studies, it is possible to conclude that (a) there is no clear pattern of sex differences in childhood, and (b) sex differences appear to favor males in adulthood. The cognitive measures used in these studies were the Wechsler scales (WAIS-R, WISC-R, WPPSI), Differential Aptitude Tests (DAT), Draw-a-Man-Test (DMT), Raven's Colored Progressive Matrices (CPM), Standard Progressive Matrices (SPM), Advance Progressive Matrices (APM), and the Brazilian Cognitive Non-Verbal Test (R-1). In general, despite better academic performance by females, cognitive differences favor males in all cognitive tasks except in some verbal domains such as language and grammar (Echavarri, Godoy, & Olaz, 2007).

For this book, we analyzed the performance of students between the ages of 14 and 15 years, an age close to the expected stability of intelligence and the age of the participants of the SLATINT Project. Table 5.3 presents the mean sex differences for each cognitive measure.

The literature is vast regarding the superiority of males in mental rotation tasks (Kaufman, 2007; Miller & Halpern, 2014; Parsons, Larson, & Kratz, 2004; Richardson, 1994); however, the relationship with mental folding is not clear (Harris, Hirsh-Pasek, & Newcombe, 2013). In our study, females performed better in the mental-folding task ($d = -.134$; 54% chance that a female picked at random will have a higher score than a male, i.e., small effect), which is partially supported by some studies (Voyer, Voyer, & Bryden, 1995). Additionally, females outperformed males in perceptual discrimination speed ($d = -.174$; 55% of probability of superiority, small effect), which also corroborates previous studies (Ellis et al., 2008). Males had better performance in crystallized (d = .146; small effect) and

Table 5.3 Sex differences in each cognitive measure administered to the SLATINT sample and effect size (Cohen-*d*)

Measures	Sex	*N*	Mean	SD	*t*	Cohen-*d*	Ability
PISA	Male	1797	.077	1.005	4.512	.146*	Crystallized intelligence
	Female	1903	−.067	.958			
SPM	Male	1867	.058	1.025	3.599	.116*	Fluid intelligence
	Female	1938	−.057	.961			
BIS_PF	Male	692	−.063	.964	−2.505	−.134*	Mental-folding task and rotation
	Female	701	.064	.939			
BIS_MF	Male	692	−.016	.969	−.221	−.012	Figural memory
	Female	701	−.004	.959			
BIS_PN2	Male	693	.139	.950	5.423	.289*	Numerical speed
	Female	701	−.136	.951			
BIS_RF	Male	692	−.100	.972	−3.252	−.174*	Perceptual discrimination speed
	Female	701	.064	.915			
BIS_PN3	Male	692	.101	.993	3.748	.200*	Numerical reasoning
	Female	701	−.091	.922			
BIS_RN3	Male	692	.220	.988	8.411	.451*	Numerical speed
	Female	701	−.216	.947			
BIS_RN1	Male	692	.037	.977	.869	.045	Numerical speed
	Female	701	−.006	.926			

Note: Cohen-*d* refers to the magnitude of a phenomenon (or effect size), and is estimated by the standardized difference between two means
*Significant differences at the 0.05 level (2-tailed)

fluid intelligence (d = .116; small effect), numerical speed (d = .451; medium effect), and numerical reasoning (d = .200; small effect), which corroborates several studies (Halpern et al., 2007; Lynn & Irwing, 2004).

5.3.2 Latin American Sex Differences in Multivariate Analysis

In the study by Flores-Mendoza et al. (2015) conducted with the sample from the SLATINT Project, mean sex differences [$t(2, 3728) = 2.352$, $p < .019$] in the SPM test (favoring males) were observed in univariate analysis. However, when other independent variables (e.g., PISA score, grade school, or SES school) were inserted in a multilevel analysis model, the influence of sex on the variance of the SPM scores disappeared.

Similarly, the study from Flores-Mendoza et al. (2017) found a slight female superiority with univariate analysis; however, at multilevel analysis, this small female effect also disappeared.

5.4 Sex Differences at *g* Level

Some researchers have asserted that sex differences are only found in studies where specific abilities were measured. If general intelligence (or *g*) is taken into consideration, these mean sex differences disappear (Aluja-Fabregat, Colom, Abad, & Juan-Espinosa, 2000; Colom et al., 2000; Dolan et al., 2006; Johnson & Bouchard, 2007; Mackintosh, 1996; Van der Sluis et al., 2006, 2008). A major systematic review commissioned by the American Psychological Association endorsed this view (Neisser et al., 1996), as did a recent review of that study (Nisbett et al., 2012).

Regarding Latin America, Flores-Mendoza et al. (2013) studied a large Brazilian sample using the BPR5 test and the SPM test. They found sex differences (favoring males) on the *g* score (extracted by the principal axis factoring of test scores) equivalent to 3.8 IQ points. Following this, a confirmatory factor analysis approach estimated mean differences (favoring males) of 3.44 IQ points or 2.7 IQ points when Mechanical Reasoning was excluded.

Data from the SLATINT Project at the *g* level were analyzed in Chap. 3. From seven potential predictors (PISA score, sex, age, kind of school, SES of school, educational level of father, and educational level of mother), three variables were found to be the most important predictors of variability of latent intelligence (or *g* score). These predictors were PISA score, sex, and age. Regarding sex, females had a lower performance than males and, for this reason, contributed negatively to predicting individual differences in *g* score. We converted the *g* score to intelligence quotient (mean = 100, SD = 15), and we found significant differences between males (n = 645, mean = 101.8, SD = 15.0) and females (n = 658, mean = 98.2, SD = 14.6) equivalent to 3.61 IQ points (Fig. 5.6).

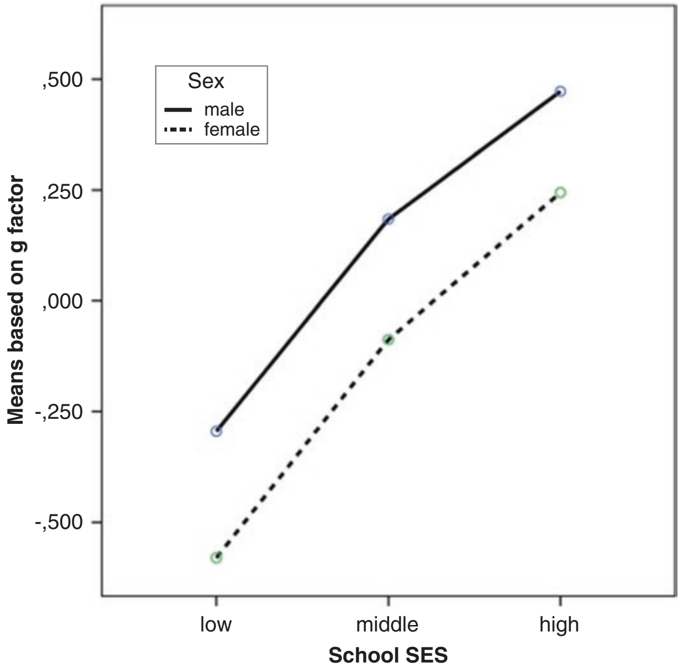


Fig. 5.6 Mean of *g* factor scores for males and females according to SES

A two-way between-groups analysis of variance was conducted to explore the impact of sex and school SES on levels of g factor, as measured by six cognitive measures. The Levene's Test of Equality of Error Variance indicated that our dependent variable (*g* factor) across the groups was equal (sig. value = .300). The results indicated a statistically significant main effect for sex [F(1, 1297) = 35.505, $p = .000$]. Also, as expected, there was a significant main effect for school SES [F(2, 1297) = 118.680, $p = .000$]. The interaction effect did not reach statistical significance [F(2, 1297) = .167; $p = .846$], i.e., sex differences were found independently of differences in school SES (or vice versa). However, we have to emphasize that the effect size of sex differences was small ($\eta^2 = .027$), while a large effect size of school SES was found ($\eta^2 = .155$). In other words, differences in school SES were considerable and would be important for practical purposes, while sex differences were negligible.

5.5 Conclusion

Cognitive sex differences are a sensitive issue. There are several controversies regarding this topic, especially if differences are concentrated in abilities critical for a successful life. Until now, published studies have provided interesting data and arguments. In spite of apparently contradictory results, there is strong evidence that females and males differ in specific abilities, which was also observed in Latin American samples. Currently, the biggest challenge for behavioral science is to define if the specific abilities, where sex differences seem to exist, are the core of general intelligence, and what are the social consequences for both sexes. Fluid intelligence, viso-spatial abilities, and numerical reasoning are crucial for STEM (Science, Technology, Engineering and Mathematics) disciplines (Lubinski, 2010; Wai, Lubinski, & Benbow, 2009; Wai, Lubinski, Benbow, & Steiger, 2010). If males outperform females in these abilities, it is reasonable to consider that sex differences in jobs related to STEM can be linked to cognitive sex differences. Likewise, if females outperform males in some verbal ability tests and non-cognitive factors such as agreeableness (Weisberg, DeYoung, & Hirsh, 2011), it is reasonable to consider that sex differences in certain jobs could be related to these abilities (e.g., psychotherapist). None of these sex differences serve as an example of a real difference in general intelligence. When we move towards this type of analysis (*g* factor), differences still remain favorable to males; however, the effect size was negligible for any practical purpose.

References

Abdel-Khalek, A. M., & Lynn, R. (2006). Sex differences on the standard progressive matrices and in educational attainment in Kuwait. *Personality and Individual Differences, 40*, 175–182.

Almeida, L. S., & Primi, R. (1998). *Baterias de Provas de Raciocínio—BPR-5*. São Paulo: Casa do Psicólogo.

Aluja-Fabregat, A., Colom, R., Abad, F., & Juan-Espinosa, M. (2000). Sex diferences in general intelligence defined as g among young adolescents. *Personality and Individual Differences, 28*, 813–820.

Caplan, P. J., Crawford, M., Hyde, J. S., & Richardson, J. T. (1997). *Gender differences in human cognition*. New York: Oxford University Press.

Codorniu-Roga, M. J., & Vigil-Colet, A. (2003). Sex differences in psychometric and chronometric measures of intelligence among young adolescents. *Personality and Individual Differences, 35*, 681–689.

Colom, R., & Lynn, R. (2004). Testing the developmental theory of sex differences in intelligence on 12–18 year olds. *Personality and Individual Differences, 36*, 75–82.

Colom, R., Juan-Espinosa, M., Abad, F., & García, L. F. (2000). Negligible sex differences in general intelligence. *Intelligence, 28*, 57–68. https://doi.org/10.1016/S0160-2896(99)00035-5

Colom, R., García, L. F., Juan-Espinosa, M., & Abad, F. J. (2002). Null sex differences in general intelligence: Evidence from the WAIS-III. *The Spanish Journal of Psychology, 5*, 29–35. https://doi.org/10.1017/s1138741600005801

Colom, R., & García-Lopez, O. (2002). Sex differences in fluid intelligence among high school graduates. *Personality and Individual Differences, 32*, 445–451. https://doi.org/10.1016/S0191-8869(01)00040-X

Dolan, C. V., Colom, R., Abad, F. J., Wicherts, J. M., Hessen, D. J., & van de Skyusm, S. (2006). Multi-group covariance and mean structure modeling of the relationship between the WAIS-III common factors and sex and educational attainment in Spain. *Intelligence, 34*, 193–210.

Dykiert, D., Gale, C. R., & Deary, I. J. (2009). Are apparent sex differences in mean IQ scores created in part by sample restriction and increased male variance? *Intelligence, 37*, 42–47. https://doi.org/10.1016/j.intell.2008.06.002

Echavarri, M., Godoy, J. C., & Olaz, F. (2007). Diferencias de género en habilidades cognitivas y rendimiento académico en estudiantes universitarios. *Universitas Psychologica, 6*, 319–329. Recuperado de http://pepsic.bvsalud.org/scielo.php?script=sci_arttext&pid=S1657-92672007000200011&lng=pt&tlng=es.

Ellis, L., Hershberger, S., Field, E., Wersinger, S., Pellis, S., Geary, D., … Karadi, K. (2008). *Sex differences: Summarizing more than a century of scientific research*. New York: Psychology Press.

Feingold, A. (1994). Gender differences in variability in intellectual abilities: A cross-cultural perspective. *Sex Roles, 30*, 81–92. https://doi.org/10.1007/BF01420741

Flores-Mendoza, C. E., Mansur-Alves, M., Ardila, R., Rosas, R., Guerrero, K., Gallegos, M., … Burga, A. L. (2015) Fluid intelligence and school performance and its relationship with social variables in Latin American samples. *Intelligence (Norwood), 49,* 66-83.

Flores-Mendoza, C., Darley, M., & Fernandes, H. B. F. (2016). Cognitive sex differences in Brazil. *Mankind Quarterly, 57*, 34–51.

Flores-Mendoza, C., Saraiva, R. B., Câmara, G. C. V., Lopes, W. M. G., Passos, A. P. C. P., Gama, A. M. V. P., … Reategui, N. (2017). Socioeconomic environment effect on inferential reasoning of Latin American students. *Salud Mental*, 40, 183-190. Doi.https://doi.org/10.17711/SM.0185-3325.2017.024.

Flores-Mendoza, C., Widaman, K. F., Bacelar, T. D., & Lelé, A. J. (2014). Propriedades psicométricas do Raven Geral no contexto de Minas Gerais. *Arquivos Brasileiros de Psicologia, 66*, 1–16.

Flores-Mendoza, C., Widaman, K. F., Rinderman, H., Primi, R., Mansur-Alves, M., & Pena, C. C. (2013). Cognitive sex differences in reasoning tasks: Evidence from Brazilian samples of educational settings. *Intelligence, 41*, 70–84.

Flores-Mendoza, C., Mansur-Alves, M., Lele, A. J., & Bandeira, D. R. (2007). Inexistência de diferenças de sexo no fator g (inteligência geral) e nas habilidades específicas em crianças de duas capitais brasileiras. *Psicologia: Reflexão & Critica*, 499–506.

Giedd, J. N., Raznahan, A., Mills, K. L., & Lonroot, R. K. (2012). Review: magnetic resonance imaging of male/female differences in human adolescent brain anatomy. *Biology of Sex Differences, 3*, 19. https://doi.org/10.1186/2042-6410-3-19

Guerrieri, G. M., Wakim, P. G., Keenan, P. A., Schenkel, L. A., Berlin, K., Gibson, C. J., … Schmidt, P. J. (2016). Sex diferences in visuospatial abilities persist during induced hypogonadism. *Neuropsychologia*, 81, 219-229.

Halpern, D. (1997). Sex differences in intelligence: Implications for education. *American Psychologist, 52*(10), 1091–1102.

Halpern, D. (2011). *Sex differences in cognitive abilities* (4th ed.). London: Psychology Press.

Halpern, D. F., Benbow, C. P., Geary, D. C., Gur, R. C., Hyde, J. S., & Gernsbacher, M. A. (2007). The science of sex differences in science and mathematics. *Psychological Science in the Public Interest, 8*, 1–51. https://doi.org/10.1111/j.1529-1006.2007.00032.x

Harris, J., Hirsh-Pasek, K., & Newcombe, N. (2013). Understanding spatial transformations: similarities and differences between mental rotation and mental folding. *Cognitive Processing, 14*, 105–115. https://doi.org/10.1007/s10339-013-0544-6

Hirnstein, M., Coloma Andrews, L., & Hausmann, M. (2014). Gender-stereotyping and cognitive sex differences in mixed- and same-sex groups. *Archives of Sexual Behavior, 43*, 1663–1673. https://doi.org/10.1007/s10508-014-0311-5

Hur, Y.-M., Nijenhuis, J., & Jeong, H. U. (2017). Testing Lynn's theory of sex differences in intelligence in a large sample of Nigerian school-aged children and adolescents (N>11.000) using Raven's Standard Progressive Matrices Plus. *Minkind Quarterly, 57*, 428–437.

Hyde, J. S., & Linn, M. C. (1988). Gender differences in verbal ability: A meta- analysis. *Psychological Bulletin, 104*, 53–69.

Hyde, J. S. (2005). The gender similarities hypothesis. *American Psychologist, 60*, 581–592.

Hyde, J. S., Fennema, E., & Lamon, S. (1990). Gender differences in mathematics performance: A meta-analysis. *Psychological Bulletin, 107*, 139–155.

Irwing, P. (2012). Sex differences in g: An analysis of the US standardization sample of the WAIS-III. *Personality and Individual Differences, 53*, 126–131.

Jackson, D. N., & Rushton, J. P. (2006). Males have greater g: Sex differences in general mental ability from 100,000 17- to 18-year-olds on the Scholastic Assessment Test. *Intelligence, 34*, 479–486. https://doi.org/10.1016/j.intell.2006.03.005

Jensen, A. R. (1998). *The g factor*. London: Praeger.

Johnson, W., & Bouchard, T. J., Jr. (2007). Sex differences in mental ability: A proposed means to link them to brain structure and function. *Intelligence, 35*, 197–209. https://doi.org/10.1016/j.intell.2006.07.003

Johnson, W., Carothers, A., & Deary, I. J. (2008). Sex differences in variability in general intelligence: A new look at the old question. *Perspectives on Psychological Science, 3*, 518–531. https://doi.org/10.1111/j.1745-6924.2008.00096.x

Kaufman, S. B. (2007). Sex differences in mental rotation and spatial visualization ability: Can they be accounted for by differences in working memory capacity? *Intelligence, 35*, 211–223.

Lubinsk, D. (2004). Introduction to the special section on cognitive abilities: 100 years after Spearman's—1904. "'General intelligence', objectively determined and measured". *Journal of Personality and Social Psychology, 86*(1), 96–111.

Lubinski, D. (2010). Spatial ability and STEM: A sleeping giant for talent identification and development. *Personality and Individual Differences, 4*, 344–351. https://doi.org/10.1016/j.paid.2010.03.022

Lynn, R. (1999). Sex differences in intelligence and brain size: A developmental theory. *Intelligence, 27*(1), 1–12.

Lynn, R. (2002). Sex differences on the progressive matrices among 15-16 year olds: Some data from South Africa. *Personality and Individual Differences, 33*, 669–673.

Lynn, R., & Irwing, P. (2004). Sex differences on the progressive matrices: A meta-analysis. *Intelligence, 32*, 481–498.

Lynn, R., Allik, J., Pullmann, H., & Laidra, K. (2004). Sex diferences on the progressive matrices among adolescents: Some data from Estonia. *Personality and Individual Differences, 36*, 1249–1255.

Lynn, R., Fergusson, D. M., & Horwood, L. J. (2005). Sex differences on the WISC-R in New Zealand. *Personality and Individual Differences, 39*, 103–114.

Lynn, R., Backhoff, E., & Contreras-Niño, L. A. (2004). Sex differences on g, reasoning and visualization tested by the progressive matrices among 7–10 year olds: Some normative data for Mexico. *Personality and Individual Differences, 36*, 779–787.

Lynn, R., Raine, T. A., Venables, P. H., Mednick, S. A., & Irwing, P. (2005). Sex differences on the WISC-R in Mauritius. *Intelligence, 33*, 527–533.

Mackintosh, N. J. (1996). Sex differences and IQ. *Journal of Biosocial Science, 28*, 559–572.

Machin, S., & Pekkarinen, T. (2008). Global sex differences in test score variability. *Science, 322*, 1331–1332. https://doi.org/10.1126/science.1162573

Miller, D. I., & Halpern, D. F. (2014). The new science of cognitive sex differences. *Trends in Cognitive Science, 18*, 37–45. https://doi.org/10.1016/j.tics.2013.10.011

Neisser, U., Boodoo, G., Bouchard, T. J., Jr., Boykin, A. W., Brody, N., Ceci, S. J., … Urbina, S. (1996). Intelligence: Knowns and unknowns. *American Psychologist*, 51, 77-101.

Nisbett, R. E., Aronson, J., Blair, C., Dickens, W., Flynn, J., Halpern, D. F., & Turkheimer, E. (2012). Intelligence. New findings and theoretical developments. *American Psychologist, 67*, 130–159. https://doi.org/10.1037/a0026699

Nyborg, H. (2005). Sex-related differences in general intelligence g, brain size, and social status. *Personality and Individual Differences, 39*, 497–509.

Parsons, T. D., Larson, P., Kratz, K., Thiebaux, M., Bluestein, B., Galen Buckwalter, J., & Rizzo, A. A. (2004). Sex differences in mental rotation and spatial rotation in a virtual environment. *Neuropsychologia, 42*, 555–562.

Richardson, J. (1994). Gender differences in mental rotation. *Perceptual and Motor Skills, 78*, 435–480.

Spelke, E. S. (2005). Sex differences in intrinsic aptitude for mathematics and science?: A critical review. *American Psychologist, 60*, 950–958.

Stark, A. K., Toft, M., Pakkenberg, H., Fabricius, K., Eriksen, N., Pelvig, D. P., … Pakkenberg, B. (2007). The effect of age and gender on the volume and size distribution of neocortical neurons. *Neuroscience,* 150, 121–130.

Van der Sluis, S., Derom, C., Thiery, E., Bartles, M., Polderman, T. J. C., Verhulst, F. C., … Posthuma, D. (2008). Sex differences on the WISC-R in Belgium and the Netherlands. *Intelligence,* 36, 48-67.

Van der Sluis, S., Posthuma, D., Dolan, C. V., de Geus, E. J. C., Colom, R., & Boomsma, D. I. (2006). Sex differences on the Dutch WAIS-III. *Intelligence, 34*, 273–289. https://doi.org/10.1016/j.intell.2005.08.002

Voyer, D., Voyer, S., & Bryden, M. P. (1995). Magnitude of sex differences in spatial abilities: a meta-analysis and consideration of critical variables. *Psychological Bulletin, 117*, 250–270.

Wai, J., Lubinski, D., & Benbow, C. P. (2009). Spatial ability for STEM domains: Aligning over 50 years of cumulative psychological knowledge solidifies its importance. *Journal of Educational Psychology, 101*, 817–835. https://doi.org/10.1037/a0016127

Wai, J., Lubinski, D., Benbow, C. P., & Steiger, J. H. (2010). Accomplishment in science, technology, engineering, and mathematics (STEM) and its relation to STEM educational dose: A 25-year longitudinal study. *Journal of Educational Psychology, 102*, 860–871. https://doi.org/10.1037/a0019454

Weisberg, Y. J., DeYoung, C. G., & Hirsh, J. B. (2011). Gender differences in personality across the ten aspects of the big five. *Frontiers in Psychology, 2*, 1–11. https://doi.org/10.3389/fpsyg.2011.00178

Chapter 6
Intelligence, Latin America, and Human Capital

Abstract Intelligence research has shown that human cognitive capital is associated with the development of nations. This chapter summarizes the results presented in previous chapters in order to analyze the quality of the human capital available in the Latin American region compared to the existing human capital in a developed country (in this case Spain). Additionally, challenges and future prospects are discussed.

Until the end of the last century, the parents of newborns used to say: "I would like my child be an engineer, architect, judge, physician, doctor, lawyer … " or "I expect my children to take over my business when they grow up." These desires are no longer applicable in the twenty-first century, at least in some developed countries. We are in a fast-moving world and the consequences of this are difficult to foresee for developing countries.

New technologies are significantly affecting countries, institutions, and citizens in a way never before seen in human history, and new on-demand occupations (e.g., data scientist, information security analyst, software architect) are beginning to impose themselves in the post-industrial model of employment. Most of these new occupations are related to STEM (Science, Technology, Engineering, and Mathematics) disciplines. Thanks to these new occupations, online business and automation are systematically eliminating middle and low complexity occupations, especially those characterized by redundancy, such as bank clerks, travel agents, warehousemen, train conductors, soldiers, mail carriers, waiters, janitors, etc. As artificial intelligence (also known as cognitive computing/augmented intelligence) is becoming more sophisticated, the next jobs to be replaced by algorithms will be those of greater complexity such as lawyers, translators, writers (journalism), some healthcare professionals, pilots, surgeons, and others.

The new model of employment (named the Fourth Industrial Revolution) will certainly provide new opportunities for some people, especially for people with high cognitive abilities; but for the majority of the population (middle and low abilities), it could cause a serious occupational disruption. In the following sections, we see how this could affect the development of nations.

C. Flores-Mendoza et al., *Intelligence Measurement and School Performance in Latin America*, https://doi.org/10.1007/978-3-319-89975-6_6

6.1 Human Capital

People were recognized as being an important factor of productivity in the first two phases of the industrial revolution (mechanical production/textile industry at the end of the eighteenth and nineteenth centuries; goods using electricity, oil, and energy in the nineteenth century and beginning of the twentieth century). However, during the 1960s (automation/third phase of the industrial revolution), economists considered human skills and knowledge as a form of capital goods. The first reason for the delay in recognizing human abilities as capital would be the initial conception that physical abilities (which were essential in the first two industrial revolutions) were distributed almost equitably in the population. Therefore, according to the early economists, these innate human abilities could not be considered in the productivity analysis. The second reason was the fear of violating human right principles (e.g., human beings treated as a material component, similar to the notion of property). However, the rapid expansion of industrialization, the increasingly sophisticated competitiveness, and economists such as Gary Becker and Theodore Schultz (American economist and Nobel Prize winner, respectively) would dispel these fears.

According to Schultz (1971), useful skills and knowledge are a part of deliberate investment (i.e., people invest in themselves), and this investment (termed human capital (HC)) is the core of the economic system. According to Becker (1975), schooling, training, or any activity that adds good habits to a person's lifetime, results in more earnings and income. Other factors of non-human capital (i.e., tangible forms) such as land, physical capital, and equipment are important to yield income, but education and knowledge allow capital to grow faster in the population. This type of investment increases opportunities and/or job alternatives and contributes to more income, wealth, and health. For this reason, HC results in economic growth for nations.

Currently, international institutions related to the country's economy such as the World Economic Forum (WEF), World Bank or Organisation for Economic Co-operation and Development (OECD) recognize the term Human Capital and its important role in the development of nations. For instance, the WEF understand HC as:

> " … the skills and capacities that reside in people and that are put to productive use … This resource must be invested in and leveraged efficiently in order for it to generate returns for the individuals involved as well as an economy as a whole." (WEF, 2015, p. 8).

Similarly, the OECD (2016) understands Human Capital as a pool of knowledge, skills, competencies, and other attributes that individuals have and are necessary and important for their own economic activity as well as for the national economy.

6.2 Wealth of Nations, Jobs, and Distribution of Human Capital

According to the International Labor Office (ILO, 2017), there are around 3.5 billion workers in the world, and 5.8% (or 201 million) were unemployed in 2017. There is doubt that the global economy will be able to create enough of jobs with quality and inclusiveness. While the number of unemployed people is increasing in developing countries (partially due to low commodity prices, low trade, and investment), evidence of structural unemployment is being observed in developed countries (long-term unemployment in Europe and the USA increased from 44.5% in 2012 to 47.8% in 2016; two-thirds of this group had been looking for a job for over 2 years).

As previously mentioned, high technology trends (or the Fourth Industrial Revolution) are widening skill gaps, and that can explain the loss of jobs. Additionally, skill gaps can threaten nations in their goal of producing wealth. At this point, an outlook on current job distribution and the existing HC measured by the World Bank (46 indicators, half of them related to educational factors, and the other half related to labor market indicators) can be useful to clarify this argument.

In 2015, the WEF conducted a large survey in nine broad industry sectors (371 individual companies) of the 15 major economies in the world (WEF, 2016). These nine broad sectors were related to Basic and Infrastructure; Consumer; Energy; Financial Services and Investors; Healthcare; Information and Communication Technology; Media/Entertainment/Information; Mobility, and Professional Services. According to this survey, there are three key drivers of change and disruption affecting industries and human resources marketplace: (1) the changing nature of work (flexible work), (2) mobile internet/could technology, and (3) processing power/big data. Demographic factors (longevity and population ageing) would affect exclusively developed countries. The WEF's survey also identified that these drivers of change are followed by strong employment growth in certain job "families" such as Architecture, Engineering/Computing, and Mathematics (i.e., job families related to STEM disciplines).

However, observing the distribution of jobs by the 15 major economies surveyed by WEF (2015), we see that around 97% of employees were working in jobs not directly related to STEM disciplines. Moreover, 36.2% of employees were working in declining jobs such as Manufacturing and Production, Office and Administrative roles, Business and Financial Operation, Sales and Related, and Construction/Extraction. When these numbers are extrapolated to the worldwide labor market, we can expect a loss of 4.8 million jobs (or two-thirds of the total lost jobs) in the Office and Administrative job family up to 2020. In all of the nations where the companies were sampled, except France, investment in reskilling current employees was indicated as the preferential strategy for dealing with the coming changes; the second most preferable strategy (this time for all nations sampled) was supporting mobility and job rotation, and the third strategy was attracting talent (female, minorities, or foreign).

If jobs related to STEM disciplines are increasing and companies indicate investment in reskilling employees as the most important strategy for dealing with the new on-demand jobs, an outlook of the preferences of university students by field of study (i.e., supply of future workers) would be useful and interesting. Table 6.1 shows data from the six top countries with high HC, two countries with intermediate HC, and data from six Latin American countries (the same Latin American countries that participated in our SLATINT (Study of the Latin American Intelligence) Project). Table 6.1 clearly indicates that in all countries, despite a declining trend in

Table 6.1 Percentage of graduate students by field of study in 2014, and business perception of quality of mathematics/science education, talent, and human capital index (HCI)

Country	First field of study	Second field of study	Third field of study	Quality of education[a]	Talent (attraction/retaining)[a]	HCI
Finland	Social Sciences, Business, Law (25.3%)	Engineering, Manufacturing, Construction (20.1%)	Health and Welfare (19.6%)	6.26	3.67/5.58	1
Norway	Social Sciences, Business, Law (26.9%)	Health and Welfare (23.4%)	Education (17.3%)	4.55	4.84/5.58	2
Switzerland	Social Sciences, Business, Law (36.9%)	Health and Welfare (13.7%)	Engineering, Manufacturing, Construction (13.1%)	5.90	6.97/5.78	3
Canada	Business, Management and Public Administration (18.4%)[b]	Humanities (15%)[b]	Social and Behavioral Sciences and Law (13.5%)[b]	5.10	5.24/4.80	4
Japan	Social Sciences, Business, Law (27.0%)	Engineering, Manufacturing, Construction (17.1%)	Humanities and Arts (14.7%)	5.09	3.31/4.41	5
Sweden	Social Sciences, Business, Law (28.0%)	Health and Welfare (23.6%)	Engineering, Manufacturing, Construction (19.3%)	4.42	4.29/4.75	6
USA	Social Sciences, Business, Law (36.4%)	Health and Welfare (17.3%)	Humanities and Arts (11.9%)	4.39	5.78/5.73	17
UK	Social Sciences, Business, Law (32.2%)	Health and Welfare (16.3%)	Humanities and Arts (16.1%)	4.29	5.87/5.03	19
Argentina	Social Sciences, Business, Law (34.5%)	Health and Welfare (17.7%)	Education (16.3%)	3.22	2.50/3.32	48
Brazil	Social Sciences, Business, Law (41%)	Education (20%)	Health and Welfare (14.5%)	2.65	3.58/3.87	78
Chile	Social Sciences, Business, Law (29.4%)	Health and Welfare (21.2%)	Education (15.8%)	3.50	4.34/4.80	45
Colombia	Social Sciences, Business, Law (48.5%)	Engineering, Manufacturing, Construction (17%)	Education (11.7%)	3.28	3.14/3.39	62
Mexico	Social Sciences, Business, Law (44.7%)	Engineering, Manufacturing, Construction (21.3%)	Education (12.5%)	2.71	3.30/3.49	58
Peru	Administration and Business (16.6%)[c]	Health and Welfare (13.4%)[b]	Economy and Accounting (11.7%)[c]	2.27	3.38/3.93	61

Source: Data extracted from WEF's reports (2015, 2016)
[a]Score between 1 (lowest) and 7 (highest)
[b]Data extracted from http://www.statcan.gc.ca/tables-tableaux/sum-som/l01/cst01/educ72a-eng.htm
[c]Data extracted from INEI (2015)

the Office, Business, and Administrative job family, Social Sciences, Business, and Law were the fields with more graduate students (future supply of workers) in 2014, with more emphasis in Latin America (average of 39.6%) than countries with a higher HC (average of 27%). The second and third field of study with more graduates were Health and Engineering for countries with a high HC, and Health and Education for Latin American countries. Surprisingly, in neither the USA nor the UK were STEM-related careers the most preferred; however, these countries seem to attract international students and successfully integrate them into the labor force.

The increase of new on-demand jobs (mostly related to STEM disciplines) and the decline of jobs related to careers paradoxically very popular in universities and colleges will create a serious conflict between demand and worker supply in the near future. Beyond reskilling employees to overcome the possible job disruption, a reshaping of education/university will be necessary. However, for both strategies to be successful, it is necessary to consider the psychological factor responsible for individual differences in academic performance and/or job training. This factor has been analyzed and discussed all the preceding chapters; this factor is human intelligence, a psychological concept successfully measured and identified as a strong predictor of social and economic differences between countries.

6.3 Intelligence of Nations

After a century of research on individual differences in mental abilities, a better understanding of the structure of intelligence and the nature and social consequences has been achieved. Individuals with greater intelligence (high IQ) are more likely to perform well in school, to obtain a university degree, a better job, occupational accomplishment, and a higher income when compared to individuals with a lower IQ (Neisser et al., 1996). However, what about differences in large groups of people (e.g. differences among nations)? Do results obtained at the aggregate level would follow the results obtained at the individual level? Apparently, the answer is positive following the publication of the book "*IQ and the Wealth of Nations*" (Lynn & Vanhanen, 2002).

As mentioned in Chap. 1, national IQ is a source of inspiration and reference for recent social, economic, and psychological cross-cultural studies. The British psychologist Richard Lynn and the Finn political scientist Tatu Vanhanen estimated the mean IQ from 185 nations from studies in which intelligence tests were administered to samples of the population. For some countries, the IQ was estimated from a variety of tests (e.g., Draw-a-Person Test or Wechsler Adult Intelligence Scales (WAIS)), but for the majority of countries (78%), the IQ was derived from the Raven Progressives Matrices (Standard and Colored Scales), which is a non-verbal reasoning test.

Some researchers (Jensen, 1998; Schweizer, Goldhammer, Rauch, & Moosbrugger, 2007) considered the Raven Progressive Matrices test as a good measure of reasoning or of the *g* factor (also called general cognitive ability), and others have emphasized its spatial nature (Colom & Garcia-Lopez, 2002; Colom, Escorial, & Rebollo, 2004).

The visuo-spatial content of this test is interesting due to its relationship with STEM careers. According to Wai, Lubinski, and Benbow (2009), this psychological-behavioral relationship was noted by Donald Edwin Super, a psychologist and career counselor, at the end of the 1950s; a period characterized by the aerospace race between USA and the ex-Soviet Union and the need for increasing the number of engineers and technicians. The Donald Super report inspired Wai et al. to compile 50 years of research about spatial ability and its relationship with STEM disciplines, and they then designed a special study. Specifically, they examined a large longitudinal dataset from the TALENT Project, in which around 400,000 students in the 9th–12th grades were assessed in 1960. Wai et al. focused on the highest degree achieved by the participants 11 years after their first psychological assessment. Two impressive results were obtained. First, higher mathematical and spatial abilities, compared to verbal ability, were found in participants who completed STEM degrees. Considering other degrees such as Education, Business, Arts, Social Science, Humanities, and Biological Science, the spatial ability was not outstanding compared to verbal and mathematics skills. Second, considering groups of means on general ability (verbal + spatial + mathematics), there was a difference of 0.40 standard deviation units between Education and Humanities (favoring Humanities), with the same difference found between Humanities and Engineering (favoring Engineering).

Would this be the same for the Latin American region? A study conducted by Flores-Mendoza, Darley, & Fernandes (2017) in Brazil compared the performance in the Advance Progressive Matrices of Raven (APM) between disciplines. The authors obtained similar results to those mentioned above. Students of Exact Sciences had a higher performance compared to students of Social Sciences and Humanities (Fig. 6.1).

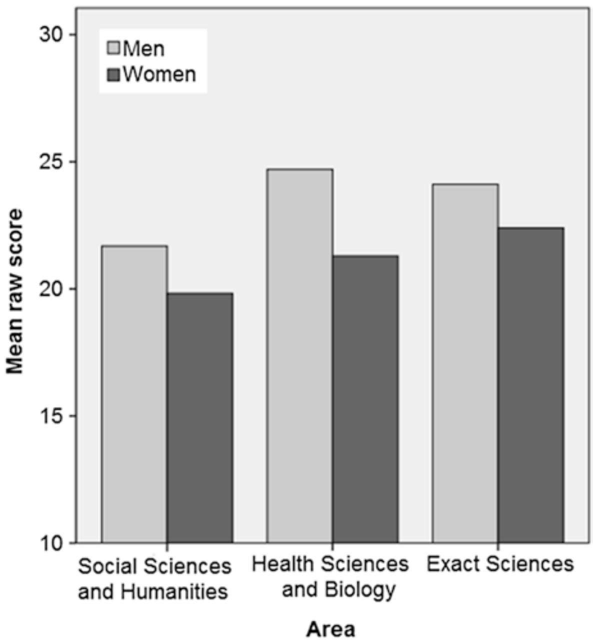


Fig. 6.1 APM mean score for each sex according to academic disciplines (figure reproduced from Flores-Mendoza et al., 2017 with permission of the publisher)

The results obtained with the Progressive Matrices of Raven test allow us to infer that, to some extent, this test demands spatial ability (beyond reasoning), an ability related to STEM disciplines. In this regard, if the IQ of nations is based on this test, the differences between nations would illustrate the difference in human capital available for dealing with the challenges of the Fourth Industrial Revolution.

Based on psychological measures (most of them relative to the Progressive Matrices of Raven), Lynn and Vanhanen (2002, 2006, 2012) elaborated a cognitive global map, which represented circa of 80% of nations of the world (see Table 6.2):

Table 6.2 Mean of IQ per region

Region	Countries	IQ
North America	USA and Canada	99
Latin America	Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Cuba, Dominican Republic, Ecuador, El Salvador, Guatemala, Haiti, Honduras, Mexico, Nicaragua, Paraguay, Panama, Peru, Uruguay, Venezuela	85
Central America	Costa Rica, El Salvador, Guatemala, Honduras, Nicaragua, Panama	82
South America	Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, Venezuela	88
Western Europe	Austria, Belgium, Germany, Luxembourg, Liechtenstein, The Netherlands, Switzerland	100
East-Central Europe	Albania, Armenia, Azerbaijan, Belarus, Bosnia, Bulgaria, Croatia, Czech Republic, European Russia, Georgia, Hungary, Moldova, Poland, Romania, Slovakia, Slovenia, Serbia, Ukraine	94
Southern Europe	Andorra, Greece, Italy, Malta, Portugal, Spain, Turkey	96
Northern Europe	Britain, Denmark, Estonia, Finland, Iceland, Ireland, Latvia, Lithuania, Norway, Sweden	98
Oceania	Australia, New Zealand	99
Middle East	Afghanistan, Arab Emirates, Bahrain, Cyprus, Egypt, Israel, Iran, Iraq, Jordan, Kuwait, Lebanon, Qatar, Syria, Turkey, Yemen	85
South Asia	Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan, Sri Lanka	81
Southeast Asia	Brunei, Cambodia, Indonesia, Laos, Malaysia, Singapore, Thailand, Timor-Leste, Vietnam	92
Far East	China, Japan, North Korea, South Korea, Mongolia, Taiwan	105
Central Asia	Tajikistan, Turkmenistan, Uzbekistan	87
Africa	46 countries	71
Southern Africa	Angola, Botswana, Comoros, Lesotho, Madagascar, Malawi, Mozambique, Namibia, South Africa, Swaziland, Zimbabwe	70
Western Africa	Benin, Burkina Faso, Cameroon, Côte d'Ivoire, Gabon, Gambia, Ghana, Guinea Bissau, Liberia, Mali, Mauritania, Niger, Nigeria, São Tome and Principe, Senegal, Sierra Leone	68
Northern Africa	Algeria, Egypt, Libya, Morocco, Sudan, Tunisia	81
East Africa	Burundi, Eritrea, Ethiopia, Kenya, Rwanda, Seychelles, Somalia, Tanzania, Uganda	71
Central Africa	Chad, Republic of Congo, Central African Republic, Democratic Republic of Congo	66

Moreover, Lynn and Vanhanen asserted that differences in national income (measured per capita by the Gross Domestic Product (GDP)) would be associated with national differences in IQ (correlation of .757 between IQ and GDP).

As expected, national differences in mean IQ became rapidly known in several scientific settings. For instance, in 2006 and 2007, papers about national IQ were the most cited by the academy according to Web of Science (Wicherts, 2009). The popularity was based on a ubiquitous and strong association between national social indexes and the mean IQ of citizens. For example, beyond wealth (Dickerson, 2006; Jones & Schneider, 2006; Whetzel & McDaniel, 2006), variance in national IQ is related to:

- Life expectancy and happiness (Kanazawa, 2006; Stolarski, Jasielska & Zajenkowski, 2015)
- Weight, after controlling for GDP per capita, trade openness, urbanization, and demographic structure (inverted U-shaped link; Salahodjaev &Azam, 2015)
- Rates of secondary education enrollment, illiteracy rate, and agricultural employment (Barber, 2005)
- Crime (Rushton & Templer, 2009)
- Tests of educational achievement (Rindermann, 2007)
- Atheism, liberalism, and monogamy (Lynn, Harvey, & Nyborg, 2009; Reeve, 2009; Kanazawa 2009a, 2009b)
- Educational achievement (Lynn, Meisenberg, Mikk, & Williams, 2007; Lynn & Mikk, 2007)
- Fertility rate (Reeve, 2009; Shatz, 2008);
- Infant and maternal mortality rate (Reeve, 2009)
- Health, HIV/AIDS rate (Vittorio, & Ostuni, 2013; Rindermann & Meisenberg, 2009)
- Social inequality (Lynn & Vanhanen, 2006)
- Government size and life satisfaction (Obydenkova & Salahodjaev, 2017)
- Deforestation (Salahodjaev, 2016)
- Production of technological knowledge and innovation (Gelade, 2008a; Jones & Schneider, 2010; Rindermann, 2012; Burhan, Razak, Salleh & Tovar, 2017; Lynn, 2012)
- Scientific productivity measured by articles published (Rindermann & Thompson, 2011)

The robust association between national IQ and notable social variables gives support for the ranking of national IQ elaborated by Lynn and Vanhanen (2002, 2006), despite the variety of tests, studies, and sample sizes analyzed. Moreover, the similarity of mean IQs among neighboring nations has been confirmed through new studies (Gelade, 2008b, Lynn & Meisenberg, 2010), which supported, in general, the trends reported by Lynn and Vanhanen. Hence, intelligence measured at the aggregate level is a potent predictor of economic, psychological, and social outcomes of nations.

According to Lynn and Mikk (2007), the association between national IQ and social variables is causal and reciprocal. In this regard, one may wonder what the IQ breaking point is for a nation achieving reasonable development. According to Whetzel and McDaniel (2006), any national mean IQ less than 90 is "a detriment to GDP regardless of its specific value" (p. 455), while Rindermann (2012) asserted that an IQ of 115 or above is significantly more relevant than an IQ of 85 for the scientific-technological excellence and economic freedom of a nation.

6.4 The SLATINT Project

As explained in Chap. 1, the SLATINT Project was designed to understand the mental abilities of Latin American people (i.e., Human Capital) and to record results that can be followed and replicated in future studies.

As said elsewhere (Flores-Mendoza et al., 2012), any interpretation of data depends on recruitment quality. Wicherts, Dolan, and van der Maas (2010) considered five sampling criteria: (1) random selection (all members of the population have an equal chance of being selected as part of the sample); (2) stratification (particularly demographic variables that characterize the samples); (3) health status (capacity of participants to respond adequately to the materials used in the study); (4) normal socioeconomic status (SES) (all socioeconomic status represented); and (5) representativeness (subset of a statistical population that accurately reflects the members of the entire population).

In the SLATINT Project, the school samples were not selected from a list of all schools in the cities (except for Belo Horizonte), but instead were recruited by convenience (or acceptance of head teachers). At least three schools from each SES level (low, middle, and high) were invited to participate in the project; however, this SES distribution (about 33% for each level) did not represent the distribution of SES in each country. On the other hand, data collection (70% between 2008 and 2009) was conducted only on students with no learning difficulties.

In general, our samples met the criteria of stratification, health status, and normal SES, but it is not possible to assert that our samples were representative of their countries. Regarding SES, there was no information about the socioeconomic stratification of schools (except for Belo Horizonte-Brazil) in the Latin American region. Therefore, the division of schools into private and public did not necessarily mean high and low SES, respectively. The city of Lima (Peru) is an example of having more private than public schools, even in poor districts. Thus, we used our knowledge of the cities and selected the schools that were representative of low, middle, and high SES. The correlation between this classification and a questionnaire (administered 1 year after finishing data collection) that assessed infrastructure and sanitary and urban conditions where the schools were located was .68. Thus, our SES classification was reasonably valid. However, we recognize that our samples did not depend on the rationale of the probability theory, and, likely, we overweight subgroups that were more readily accessible. Thus, our samples of Latin American students were non-probabilistic (proportional quota sampling type) and they may not represent the Latin American population well.

6.4.1 Samples and Quality

In order to analyze a sample exclusively comprised of Latin American students, the following groups were deleted from the dataset: the Spanish sample, students aged 13 and 16 years, and immigrant students studying in the Latin American region. The flow chart (Fig. 6.2) indicates the final Latin American sample analyzed.

The total sample was comprised of 3572 Latin American students aged between 14 and 15 years (M = 14.4, SD = .48), 51.2% females, 69.5% attending the ninth grade, 52.4% enrolled in 63 schools (54% private schools), 35% enrolled in low SES schools, 35.4% enrolled in middle SES schools and 29.6% enrolled in high SES schools. Table 6.3 shows the frequencies observed for each sub-sample.

In addition to the lack of representativeness of our samples, we wanted to quantify how similar or different the sub-samples were with regard to criteria that could increase or diminish their mean score in the SPM test. According to previous studies (Neisser, et al., 1996; Nisbett et al. 2012), six conditions could change the mean score of the SPM test: developed and urban areas (i.e., geography), private schools, male sex, high socioeconomic level, compulsory school before 7 years old, and higher education level of parents. Thus, we designed a scale defining "0" as expected

Fig. 6.2 Latin American sample analyzed

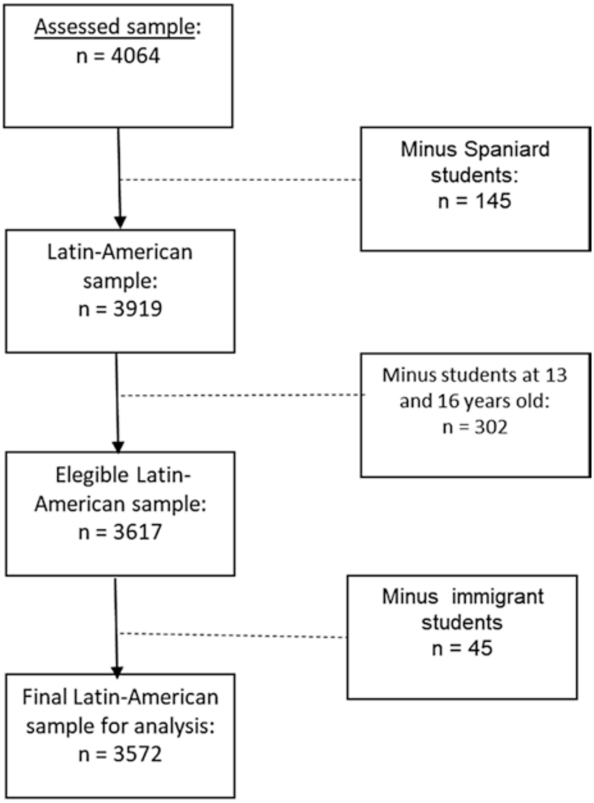


Table 6.3 Contingency table of frequencies observed for SES-school, type of school, sex, age, school grade, and educational level of mother

Variables		Rosario	Belo Horizonte	Santiago	Bogotá	Mexico City	Lima	Sum
SES school	Low	183 (33.2%)	232 (36.2%)	189 (37.0%)	197 (30.5%)	200 (30.8%)	248 (43.2%)	1249 (35.0%)
	Middle	183 (33.2%)	212 (33.1%)	176 (34.4%)	337 (52.2%)	227 (35.0%)	130 (22.6%)	1265 (35.4%)
	High	186 (33.7%)	196 (30.6%)	146 (28.6%)	112 (17.3%)	222 (34.2%)	196 (34.1%)	1058 (29.6%)
Type of school	Public	315 (57.1%)	494 (77.2%)	189 (37.0%)	197 (30.5%)	200 (30.8%)	248 (43.2%)	1643 (46.0%)
	Private	237 (42.9%)	146 (22.8%)	266 (52.0%)	449 (69.5%)	449 (69.2%)	326 (56.8%)	1873 (52.4%)
	Other	0 (0.0%)	0 (0.0%)	56 (11.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	56 (1.6%)
Sex	Female	273 (49.5%)	296 (46.2%)	268 (52.4%)	296 (45.8%)	319 (49.2%)	290 (50.5%)	1742 (48.8%)
	Male	279 (50.5%)	344 (53.8%)	243 (47.6%)	350 (54.2%)	330 (50.8%)	284 (49.5%)	1830 (51.2%)
Age	14	274 (49.6%)	390 (60.9%)	437 (85.5%)	397 (61.5%)	402 (61.9%)	299 (52.1%)	2199 (61.6%)
	15	278 (50.4%)	250 (39.1%)	74 (14.5%)	249 (38.5%)	247 (38.1%)	275 (47.9%)	1373 (38.4%)
Grade	Eighth	79 (14.3%)	622 (97.2%)	0 (0.0%)	89% (13.7%)	25 (3.9%)	0 (0.0%)	815 (22.8%)
	Ninth	309 (56.0%)	18 (2.8%)	511 (100%)	480 (74.3%)	624 (96.1%)	539 (93.9%)	2481 (69.5%)
	Tenth	164 (29.7%)	0 (0.0%)	0 (0.0%)	77 (11.9%)	0 (0.0%)	35 (6.1%)	276 (7.7%)
Mother education	Primary	129 (24.9%)	219 (36.3%)	42 (8.4%)	103 (17.0%)	38 (6.3%)	22 (4.1)	553 (16.4%)
	High School	185 (35.7%)	190 (31.4%)	169 (33.9%)	241 (39.7%)	117 (19.5%)	206 (37.8%)	1108 (32.8%)
	College	204 (39.4%)	195 (32.3%)	288 (57.7%)	264 (43.4%)	445 (74.2%)	317 (58.2%)	1713 (50.8%)

condition, "+1" if the condition would increase the SPM mean score, and "−1" if the condition would decrease the SPM mean score.

Table 6.4 shows that four samples were recruited from the most developed cities (Santiago, Bogota, Mexico City, and Lima). In this case, a positive point was assigned to these samples and negative point for the other two (Rosario and Belo Horizonte). For the other variables, one sample *t*-test between percentages (using software StatPac, version 4.0) was conducted for each sample. Regarding the type of school, four samples (Santiago, Bogota, Mexico City, and Lima) had significant proportions of private schools ($p < .001$). These samples received a positive point, while the others received a negative point. Two samples (Belo Horizonte and

Table 6.4 Factors that under-/overestimated the mean SPM score within samples

	Rosario	Belo Horizonte	Santiago	Bogota	Mexico City	Lima
Geography	−1	−1	0	0	0	0
Type of school	−1	−1	+1	+1	+1	+1
Sex	0	−1	0	−1	0	0
SES individual	−1	−1	0	−1	0	0
Years of school	0	−1	0	0	0	0
Father education	0	0	+1	0	+1	+1
Total score	−3	−5	+2	−1	+2	+2

Bogota) had more female students. These samples received a negative point, while the others received 0 points due to the balanced proportion of females and males (Rosario, Mexico City, and Lima) or non-significant proportion differences (Santiago). Analysis of variance (ANOVA) with post-hoc Tukey HSD (Honestly Significant Difference) indicated that three samples had a significant lower mean of individual SES (Rosario, Belo Horizonte, and Bogotá). These samples received a negative point, while the others received 0 points due to non-significant mean differences among them. Regarding compulsory school before 7 years of age, only the sample of Belo Horizonte did not meet this criterion. This sample received a negative point, while the others received 0 points due to all starting compulsory school at the age of six. Finally, regarding the father's education, three samples (Santiago, Mexico City, and Lima) had the highest percentage of fathers with high education. These samples received a positive point, while the others received 0 points due to the balanced proportion of education levels.

The total score indicated −3 points for the sample from Rosario, −5 points for the sample from Belo Horizonte, 2 points for the sample from Santiago, −1 point for the sample from Bogota, 2 points for the sample from Santiago, Mexico City, and Lima (see Table 6.4). Therefore, samples of Belo Horizonte, Rosario, and Bogota could have their means underestimated (in this order), while samples of Mexico City, Lima, and Santiago could have their mean overestimated. The obtained score refers to comparison within and between sub-samples, .i.e., it does not refer to representativeness comparison between countries.

6.4.2 The SPM Test

As previously mentioned, the majority of studies on national IQ are based on cognitive national achievement in the Standard Progressives Matrices of Raven (SPM) test. Moreover, the IQ of 78% of countries analyzed by Lynn and Vanhanen (2002) was based on performance in the SPM test. It is an easy and economical test, presumed to be a good measure of Spearman's *g* factor (Jensen, 1998). It contains 60 items/questions, in five series of 12 items each. The coefficient alpha for the total sample of this study was .900 (the lowest was .856 for the Bogota sample, and the highest was .916 for the Rosario sample). However, there is a serious problem: SPM scores are not normally distributed in most samples. Studies on Brazilian samples

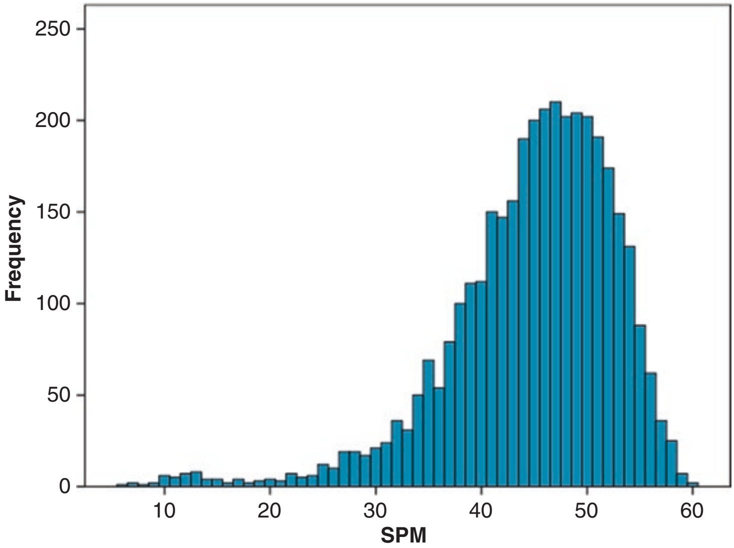


Fig. 6.3 Distribution of the SPM scores for the Latin American sample

(Flores-Mendoza, Widaman, Bacelar, & Lelé, 2014; Flores-Mendoza et al., 2012) and Peruvian samples (Millones, Flores-Mendoza, & Rivalles, 2015) indicated non-normal distribution of the scores of the SPM test.

In this chapter, we examine the distribution of SPM scores. We observed that the distribution had a significant negative skewness (−1.299/.041) or a long left tail. Thus, our dataset shows a departure from symmetry. In addition, we found positive kurtosis (2.929/.082), which indicates that, relative to a normal distribution, the observations are more clustered at the center of the distribution (Fig. 6.3). In order to verify how far our data departed from the normal distribution, we calculated the effect size from D'Agostino's K-squared test of normality [DK = skewness (Stat/SE)^2 + kurtosis (Stat/SE)^2 follows X^2 with df = 2]. The effect size is calculated by dividing the X^2 of DK by the total number of cases. The effect size obtained was 0.32, which means a strong effect, i.e., the field distribution was very different from the normal distribution. Even using the new approach to determine skewness in non-normal distributions proposed by Gunver, Senocak, and Vehid (2017), the parameters pointed out a distribution largely skewed to the left ($G = -1.505$; $O = 45.19$; σRight = 6.02; σLeft = −8.17).[1]

[1] The new approach eliminates the weaknesses of estimating skewness based on arithmetic mean and standard deviation in non-normal distributions. This new method called "GRiS method" determines the Coefficient of Skewness (G) by checking the balance of load distributions of both sides of the dataset according to the median. If the data stack is symmetrical around the median, G should be equal to −1. If the data stack is skewed towards the left of the median, G will be smaller than −1, and if the data stack is skewed towards the right of the median, it will be bigger than −1. The GRiS mean is represented by 'O', and 'σ' are the deviations generated by the extreme values relative to the GRiS mean.

A left-skewed distribution (also called negatively-skewed distribution) also means that the SPM scores fall towards the higher side of the scale and there were very few low scores (Fig. 6.3). In other words, the test was relatively easy for a large number of students. The item characteristic curve (ICC) based on the field of Item Response Theory (IRT) is another way of observing the level of difficulty of the SPM items. Figure 6.4 shows many items with low discrimination and little difficulty, i.e., students with low ability (e.g., Theta of −1.5) had a high probability (above 50%) of responding correctly to many items.

However, there is a problem with the unidimensionality of the SPM test, which is one assumption of IRT. Only one latent trait is considered in the IRT analysis. Several studies have pointed out that the SPM test measures at least two or three factors (Van der Ven & Ellis, 2000; Mackintosh & Bennett, 2005). In Chap. 4, we presented the result of a categorical principal components analysis using the total sample ($n = 3919$), and we found nine factors with eigenvalues above 1, explaining 38.1% of the variance. However, only two dimensions had an acceptable internal consistency coefficient (Cronbach's alpha) equivalent to 0.911 for the first dimension and 0.693 for the second dimension. Analyzing the Latin American sample ($n = 3570$) without immigrant students and students aged 13 and 16 years (see flowchart in Fig. 6.1), we found similar results. As presented in Chap. 4, 16 items (A12, B12, C6, C7, C8, C10, C11, E1, E2, E3, E4, E5, E6, E7, E8, and E9) seemed to be the set of SPM items with an acceptable fit to the data [CFI = 0.932; TLI = 0.922; RMSEA = 0.044]. After this transformation, higher ICCs are presented (Fig. 6.5).

The test information curve (Fig. 6.6) used to evaluate the performance of the SPM test indicated that the amount of information for the SPM-56 items was maximum (16) at an ability of −1.5 with a range of −2 to −1.5; i.e., within this range, ability is estimated with some precision. Outside of this range, the amount of information decreases rapidly and the corresponding ability levels are not estimated accurately, especially for high levels of ability. For the SPM-16 items, there was a maximum of information (8) at an ability level of 0 (range of −0.5 to 0.5). Therefore, compared to the longer version of the SPM test, the maximum value of the test

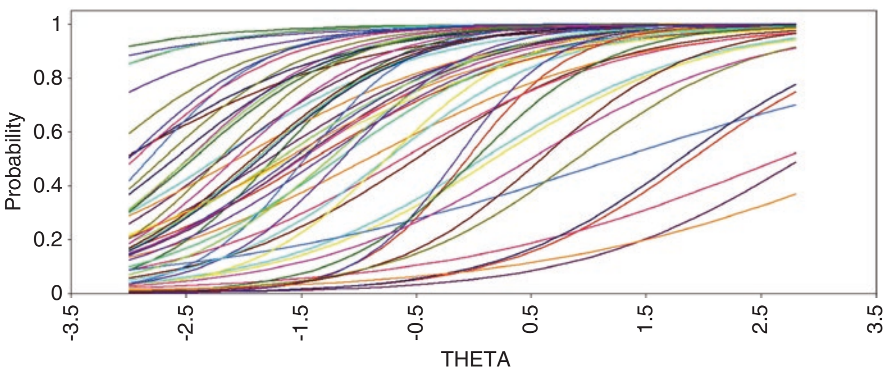


Fig. 6.4 ICC for the 56 items of the SPM test (first four items presented no variance)

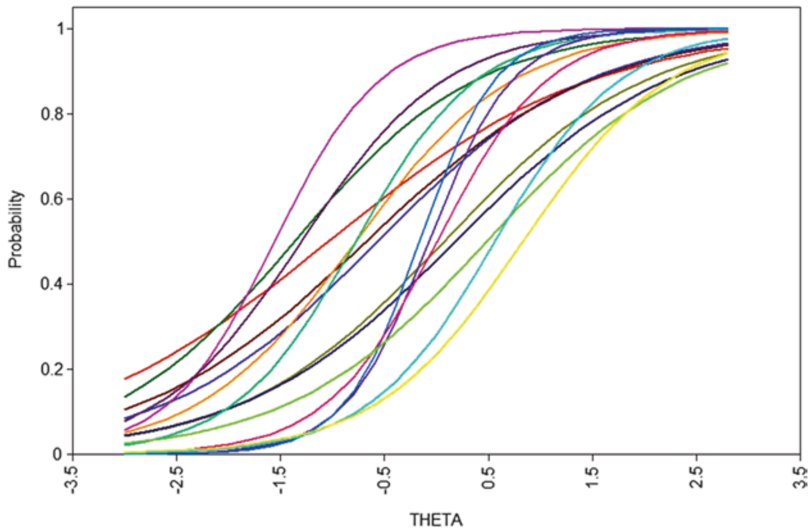


Fig. 6.5 ICC for the SPM-16 items version

information function for the shorter version is modest; however, the ability was estimated with more precision near the center of the ability scale. In other words, the larger version (56 items) provides more information for lower ability levels, while the shorter version (16 items) provides more information regarding abilities at the middle level.

Besides the uniqueness problem of the SPM test and non-normal distribution, there is criticism regarding whether the SPM scores represent a valid measure of general intelligence (or *g* factor), which is considered a latent variable (Wicherts, Dolan, & van der Maas, 2010).

As mentioned before, most of the specialized literature in the field of national intelligence is based on samples of individuals (unrepresentative of the relevant populations) that used versions of the Progressive Matrices of Raven tests such as Colored (CPM), Standard (SPM), or Advanced Matrices (APM). In order to ensure a fair comparison between our study and others, we will use the SPM scores to estimate the position of our samples on the international IQ scale. However, the reader should keep in mind the previous information about the questioned unidimensionality of the SPM test.

6.4.3 Estimating the "Greenwich-IQ"

Research on national cognitive differences uses British results (1979) on SPM as a "Greenwich-IQ" norm (IQ-scale: M = 100, SD = 15). That means people in Great Britain are set at an average IQ of 100. Considering that British children have raised

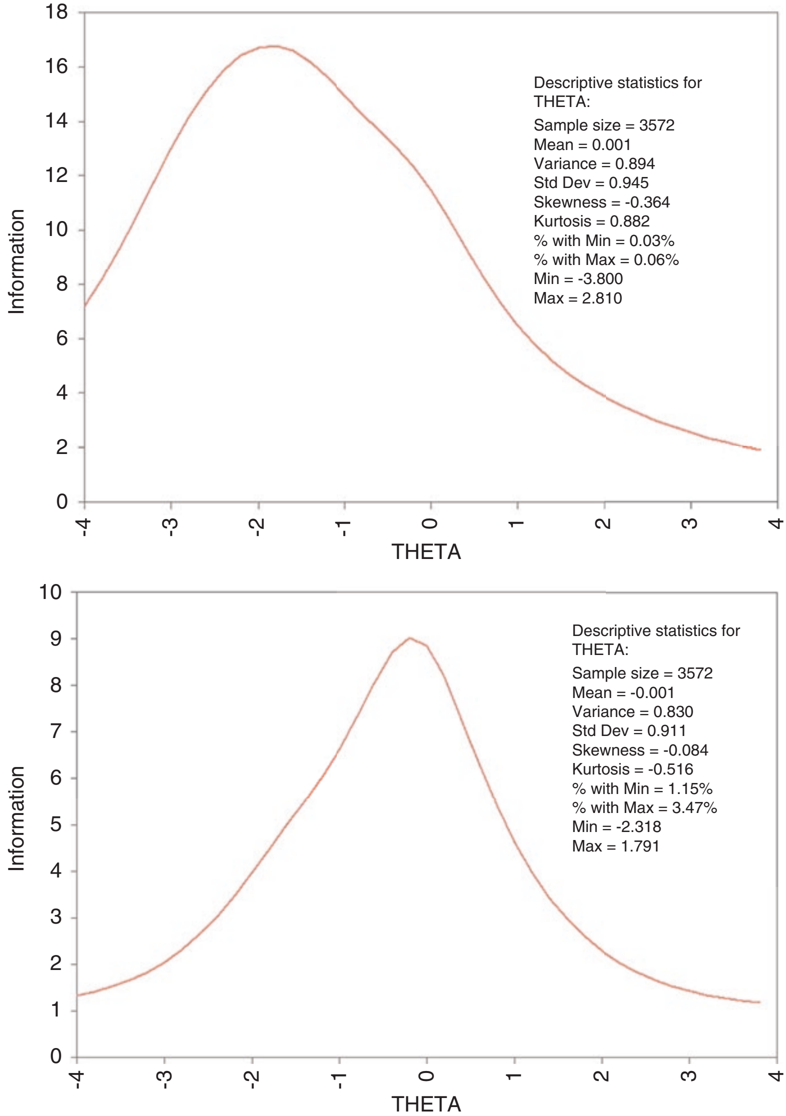


Fig. 6.6 Information test for the SPM-56 items (**a**) and for the SPM-16 items (**b**)

their mean IQ since 1979, causing the Flynn Effect (generational cognitive gains), a correction for current IQ is necessary. Nevertheless, the British IQ increase seems to be inconsistent. Recently a decline in the IQ was noted in the UK (Lynn, 2009). For this reason, we accepted the arguments presented by Rindermann and te Nijenhuis (2012) and we used a correction of 2.07 points per decade. It should be noted that the 1979 British norms for calculating the IQ of a nation are used when the SPM test has been used in children and adolescents, aged between 7 and 15 years. However, if the SPM test is used in adults, the 1993 USA norms must be used for the calculation. According to Lynn (2006), the estimative of IQ must consider the Flynn effect (2 points per decade), and a correction related to the performance of American ethnic groups (minus 2 points). For example, if a data collection in adults was performed in the year of 2013, and the mean obtained was 52 points in the SPM test, the percentile based on the 1993 USA norms would be 50 (or IQ = 100). Considering the adjustment for the Flynn effect (0.2 × 20 years = 4 points), the average IQ of the group would be 96. Moreover, considering the effect of ethnic performance on American norms (minus 2 points), the final average IQ would be 94. By the other hand, if the CPM version was used (a version of the Matrices Progressive of Raven for children with age between 5 and 11 yrs), it would be possible to convert the CPM raw score to the SPM raw score, as proposed by Raven, Raven, and Court (2000; Table CPM27).

Our data were collected between the end of 2007 and 2011 (72% in 2008–2009) using the SPM test in adolescents. Thus, the adjustment (or deduction of IQ points due to the Flynn effect) would be: 6.21 IQ points [2.07 × 3 decade = 6.21]. We prefer to round this value to 6 points to make calculations easier and results easier to understand.

Table 6.5 shows descriptive statistics (including median), the mean IQ estimated (adjusted and unadjusted) for the samples from six Latin American cities based on arithmetic mean (somewhat debatable when data does not have a normal distribution), the number of factors that permitted under- or overestimation of the IQ, and the IQ estimated by Lynn and Vanhanen (2002, 2006) for each city.

Considering the presence of factors in each sample that could increase or diminish the mean score on the SPM test, Table 6.5 indicates that the mean IQ for samples from Rosario (probably underestimated) and Santiago (probably overestimated) are slightly different from the values given by Lynn and Vanhanen (2006). Note that the studies on which Lynn and Vanhanen estimated the national IQ for Argentina and Chile were old; they were sometimes non-traceable or they referred to non-representative samples of the country. However, regarding Argentina, there is a study conducted in 1998 on a representative sample of the school students from the city La Plata (Flynn & Rossi-Casé, 2012). According to this study, a mean SPM score around 47 was found for students between 14 and 15 years of age, which was equiva-

Table 6.5 Descriptive statistics of performance on the SPM test and IQ estimation for Latin-American samples

	SPM				IQ based on Mean		Under-/Over	Lynn National
Samples /Cities	*n*	Me	SD	Md	IQ Unadj	IQ Adj	estimation	IQ estimate
Rosario	552	43.6	8.70	45.0	94 (P34)	88	−3	93
BH	640	42.6	8.82	44.0	92 (P29)	86	−5	87
Santiago	511	45.6	7.60	47.0	97 (P41)	91	+2	90
Bogotá	646	43.0	6.83	44.0	92 (P29)	86	−1	84
Mex. City	649	46.8	6.59	48.0	99 (P46)	93	+2	88
Lima	574	47.5	7.26	49.0	100 (P50)	94	+2	85
Total	3572	44.8	7.90	46.0	95 (P37)	89		

Note: negative signal = under estimation; positive signal = over estimation. Digits in the column represent the number of factors present in the samples that could allow an under-/overestimation of the mean IQ lent to an IQ of 100 in the context of British norms of 1979. Adjusting for the Flynn effect, the mean IQ should be reduced to around 96 (2 points per decade). It is worth noting that in 1998, the city La Plata had more private than public schools (52% and 48%, respectively), and the monthly family income was a little higher than observed elsewhere in the country. Therefore, as opposed to the IQ estimated for students of Rosario, the IQ of La Plata could be overestimated. Considering both estimates, it is possible to infer that the IQ of Argentina could be between the IQs 96 (La Plata) and 88 (Rosario), and possibly close to the Lynn and Vanhanen estimate.

In the case of Chile, the study of Marincovich et al. (2000), the same used by Lynn and Vanhanen for estimating the IQ of Chile, published SPM scores obtained between 1986 and 1987 by a representative sample of students from the Metropolitan Region of Chile, aged between 11.0 and 18.5 years. For 14-year- olds, the median obtained was 45, which was equivalent to an IQ of 95 in the context of the British norms of 1979. Adjusting for the Flynn effect, the mean IQ should be reduced to 93 or 94 (0.2 points × 8.5 years = 1.7). Therefore, if the median is considered, it is an estimate close to our value.

The IQ estimated for the Belo Horizonte sample was similar to the estimate for the Bogota sample. Only the Brazilian IQ estimate was close to the Lynn and Vanhanen estimate. There is no Brazilian study based on a nationally representative sample using the Progressive Matrices of Raven. However, there are several studies conducted on non-probabilistic samples, perhaps some of them representative of only specific areas such as São Paulo (Angelini, Alves, Custódio, Duarte, & Duarte, 1999) or Porto Alegre (Bandeira, Alves, Giacomel, & Lorenzatto, 2004), which used the Colored Progressive Matrices (CPM). Lynn and Vanhanen used the study of Angelini et al. (1999) for their Brazilian IQ estimate. To our knowledge, Flores-Mendoza et al. (2012) conducted the largest study on a non-probabilistic sample that used the SPM test. These authors analyzed the cognitive performance of 1192 Brazilian adults (46% males), aged between 16 and 65 years, and 76.6% born in the Minas Gerais state (23.4% were from ten Brazilian states). The results, similar to ours, indicated a distribution with significant negative skewness (−1.678/0.071) and positive kurtosis (3.369/0.142), which meant a non-normal distribution. The mean SPM score was 48.6, which according to the American norms of 1993 (and after the Flynn effect is controlled) represented an IQ of 89. We had access to the dataset of this study and we verified that the median was 51, which according to the American norms of 1993 and after adjustment of the Flynn effect represented an IQ of 93. If the norms of the CPM found for São Paulo city were considered (Angelini et al., 1999), we can observe that at a percentile of 50 (IQ = 100), the raw scores achieved by Brazilian children were below the performance of American children (Table 6.6). The CPM mean score (19.6) converted to the SPM score (Raven, Raven, & Court,

Table 6.6 CPM raw score at percentile 50 of the samples from the USA and Brazil

Samples	6	7	8	9	10	11
USA norms—1986	16	20	24	27	29	31
São Paulo (Brazil) norms—1987	15	17	19	21	24	27
Porto Alegre (Brazil) norms—1994–1998	17	19	21	25	26	28

2000; Table CPM27) would be equivalent to 20. Using the 1979 British norms, we arrived at a percentile of 16 for 8.5 years old or IQ equivalent to 85. After adjustment for the Flynn effect [0.2 points × 8 years (1987–1979) = 1.6], the final IQ should be reduced to 83 or 84. On the other hand, if the norms of the CPM posited for Porto Alegre city were considered (Bandeira et al., 2004), we can observe that at a percentile of 50 (IQ = 100), the raw scores achieved by children from Porto Alegre city were less inferior to the performance of American children than children from São Paulo city (Table 6.6). There is no information of when the Porto Alegre city study was conducted; however, another paper by the same first author (Bandeira, Costa, & Arteche, 2012) stated that the Porto Alegre study was conducted between 1994 and 1998. Converting the CPM mean score to the SPM score, the mean value would be equivalent to 22. Using the 1979 British norms, we arrived at a percentile of 20 for 8.5 years old or IQ 88. After adjustment for the Flynn effect [2 points × 1.7 decades (1979–1996) = 3.4 points], the final IQ should be reduced to 84 or 85. It is worth noting that while the São Paulo study was conducted in public and private schools, the Porto Alegre study was only conducted in public schools. If students from private schools had participated, the average IQ of Porto Alegre would probably be higher.

It is necessary to consider that the IQ estimated for the Belo Horizonte students was greatly underestimated (see Table 6.4). Thus, the IQ of Brazil could be between 89 and 93 (i.e., an IQ value higher than Lynn and Vanhanen's estimate). Regarding Colombia, we were not able to find any study on large samples using the SPM test. Perhaps our study is the first to publish large data of cognitive performance of Colombian students using this test.

For Mexico and Peru, the estimated IQ for samples from these countries was unexpectedly high. Regarding Mexico, we were not able to find any study on a representative or large sample using the SPM test. However, there is a study conducted by Lynn, Backhoff, and Contreras (2005) on a sample of 920 children supposedly representative of the town of Ensenada, Baja California, Mexico. Lynn et al. reported a mean IQ of 98 for white Mexicans, 94 for Mestizos, and 83 for indigenous Mexicans. Considering the whole country, the mean IQ of Mexico would be 88 (Lynn & Vanhanen, 2012), an estimate lower than that found in the SLATINT Project. Another study conducted by Nista and Ibarra (2014) on 665 indigenous Yaqui children, indicated that the mean performance in 2011/2012 of these children was inferior to the performance of American children in 1986. Table 6.6 shows the raw scores at a percentile of 50 for each age of American and indigenous Mexican children. Additionally, scores from Mexican normative data informed by Nistal and Ibarra are presented. If the CPM score of indigenous children was converted to the SPM score (Raven et al., 2000; Table CPM27), the mean CPM raw score (21) would be equivalent to 21 SPM score. In the case of normative data, the mean CPM raw score (24.6) would be equivalent to 27 SPM score. Compared to the 1979 British norms, we arrived at a percentile of 17 for 8.5 years old or an IQ equivalent to 86 for indigenous children. Adjusting this value for the Flynn effect [2 points × 2.5 (decades) = 5.0], the final IQ should be reduced to 81. In the case of Mexican normative data, we arrive at a percentile of 35 for 8.5 years old or an IQ equivalent to 94. Adjusting this value for the Flynn effect [2 points × 1.4 (decades) = 2.8], the final IQ should be reduced to around 91, an estimate closer to the estimate in the

Table 6.7 CPM raw score at percentile 50 of the samples from the USA and Mexico

Samples	6 years	7 years	8 years	9 years	10 years	11 years
USA norms—1986	16	20	24	27	29	31
Indigenous Yaqui Mexico—2011/2012	16	18	19	22	24	25
Normative Mexican data—2000/2001	19–20	19–20	21–24	24–25	28–29	30–31

Table 6.8 CPM raw score at percentile 50 of the samples from the USA and Peru

Samples	6 years	7 years	8 years	9 years	10 years	11 years
USA norms—1986	16	20	24	27	29	31
Cuzco (Peru) norms—1996	18	20	24	27	29	30
Lima (Peru) norms—2001	17	23	26	28	29	32

SLATINT Project. Our study is the first to publish a large dataset of cognitive performance of Mexican students using the SPM test. Replication would be necessary.

Regarding Peru, the study conducted by Millones, Flores-Mendoza, and Rivalles (2015) on a representative sample of 1097 school children (mean age = 11.6 years) of the city of Lima, using the SPM test, estimated a mean IQ of 91. However, considering previous Peruvian studies, Millones et al. estimated an IQ of 78 for people of the Andean region, and an IQ of 66 for people of the Amazonian region. Therefore, at the national level, Millones et al. arrived at an IQ of 84 for Peru, the same value estimated by Lynn and Vanhanen. Another study conducted by Arias (2014) on a sample of 467 students of a private university (58.6% males; mean age = 20.6 years) of the city of Arequipa (South of Peru and Peru's second most populated city) and assessed with the SPM test, found a mean of 43 (median = 44). This study was conducted around 2013. According to the 1993 American norms, the IQ equivalent would be 83 (percentile 12), which should be reduced to 79 due to the Flynn effect (reduction of 2 points per decade). Another study conducted by Quiroz, Chávez, and Holgado (1998) on a representative sample of children of the Cuzco city (Andean city) used the CPM test. The aim was to develop norms for this city. The results indicated that the mean performance in 1996 of children of the Cuzco city was similar to the performance of American children shown a decade before (1986) (Table 6.7). If the CPM mean score of children of the city of Cuzco was converted to the SPM score (Raven et al. 2000; Table CPM27), this score (25.5) would be equivalent to 28. Using the 1979 British norms, we arrived at a percentile of 38 for 8.5 years old or an IQ of 95. Adjusting this value for the Flynn effect [2 points × 1.7 (decades) = 3.4], the final IQ should be reduced to around 91. Table 6.8 shows results from another study conducted by Vásquez (2014) with a representative sample of school children of the city of Lima. This study indicated a mean score of 25.03 on the CPM test, almost the same mean obtained by the sample of children living in the Cuzco city (25.5). Unfortunately, the conversion of CPM raw scores into SPM raw scores (Raven et al. 2000; Table CPM27) appears to be unsatisfactory (Rushton & Čvorovic, 2009).

Thus, we are more inclined to accept that the mean IQ of Mexico and Peru could be higher than that estimated by Lynn and Vanhanen (2012), but smaller than the IQ estimated by the present study.

6.5 Immigrants

In the 21st century, as the world globalizes, people are moving more and more for economic or other reasons. According to the United Nations Human Rights (http://www.ohchr.org/EN/Issues/Migration/Pages/MigrationAndHumanRightsIndex.aspx) around 244 million people live outside their country of origin. For obvious reasons, developed countries receive more immigrants than developing countries.

Currently, there has been renewed interest regarding cultural influences on the development of intelligence, especially on people from different cultural backgrounds living in the same country. Results of studies in this direction pointed out lower performance of immigrants from developing countries than natives from developed countries (te Nijenhuis, Tolboom, Resing, & Bleichrodt, 2004; te Nijenhuis, de Jong, Evers, & van der Flier, 2004; te Nijenhuis, Willigers, Dragt,& van der Filer 2016). Here, we realized an opportunity for replicating these results with our own dataset.

First of all, we were conscious that our sample of immigrants was small. This was expected, as Latin America is the region with the lowest percentage of international migrants (http://www.un.org/en/development/desa/population/migration/data/estimates2/estimatesgraphs.shtml?0g0). Because of this, caution should be excercised when using the results from our study.

There were 81 immigrant students in the total sample dataset. Of these, 51 (or 63%) were Latin American students, and 30 (47%) were non-Latin American (Table 6.9). Some of the immigrants were studying outside of their countries in the Latin America region, and some were studying in Spain. The precise distribution was: 19 Latin American students studying in the Latin American region, 32 Latin American students studying in Spain, 26 non-Latin American students studying in the Latin American region, and four non-Latin American students studying in Spain. We could not verify if the country of birth also meant the origin of the student's parents (e.g., Italian student of Italian parents studying in the Latin American region or Italian student of Latin American parents studying in Latin America). Thus, we do not know if the student's family moved away to another country. According to the proportion of answers regarding native language, 100% of Latin American students who were studying in the Latin American region spoke Spanish (with the exception of a Brazilian student); however, 69% of non-Latin American students also indicated Spanish as their native language. Among these, there were six Japanese students with Japanese surnames, who confirmed their Japanese origin. Reconsidering this fact, the proportion of students who were non-Latin American students and had Spanish as their first language diminished to 46%. Therefore, caution is necessary in the interpretation of results.

An independent-samples *t*-test was conducted to compare the SPM scores for the Latin American immigrant group and other immigrants. There was a significant difference in scores between the Latin American immigrant group (M = 46.9, SD = 6.93), and other immigrants [M = 50.3, SD = 4.75; $t(79) = -2.347$, p = .021], favoring the last group. The magnitude of the differences in the means was moder-

Table 6.9 Country of origin of the immigrant students present in the SLATINT dataset and their scores on the SPM test

Country of Birth	*n*	%	SPM score*
Argentina	4	4.9	49.3
Australia	1	1.2	52.0
Bolivia	3	3.7	46.0
Brazil	1	1.2	43.0
Chile	4	4.9	50.8
Colombia	7	8.6	47.4
Costa Rica	1	1.2	15.0
Dominican Republic	1	1.2	53.0
Ecuador	22	27.2	47.0
France	2	2.5	51.0
Guatemala	1	1.2	49.0
Israel	1	1.2	43.0
Italy	1	1.2	54.0
Japan	6	7.4	49.3
Korea	2	2.5	55.0
Peru	4	4.9	47.8
Puerto Rico	1	1.2	30.0
Romania	4	4.9	48.5
Spain	1	1.2	48.0
Switzerland	3	3.7	49.3
Uruguay	1	1.2	55.0
USA	9	11.1	51.3
Venezuela	1	1.2	55.0
Groups			
Other Immigrants	30	37.0	50.3
Latin America Immigrants	51	63.0	46.9
Total sample	81	100.0	48.2

Note: *SPM score = raw score (mean raw score for group of participants)

ate (d_{Cohen} = .54). Figure 6.7 shows the boxplot of the SPM scores for both groups of immigrants. Even after eliminating outlier points (n = 6), significant differences in scores remained between the Latin American immigrant group (M = 47.9, SD = 4.7), and other immigrants [M = 51.9, SD = 2.1; $t(73) = -4.118$, p = .000], favoring the last group. It must be clarified that there were no significant differences between the two groups related to individual SES, sex, or SES of schools.

The next step was to compare the cognitive performance of Latin American students who were studying in the Latin America region (or Group 1 (n = 26)), Latin American students who were studying in Spain (or Group 2 (n = 32)), and other immigrants who were studying in the Latin American region (or Group 3 (n = 26)). Other immigrants studying in Spain were not analyzed because they made up a very small sample (n = 4).

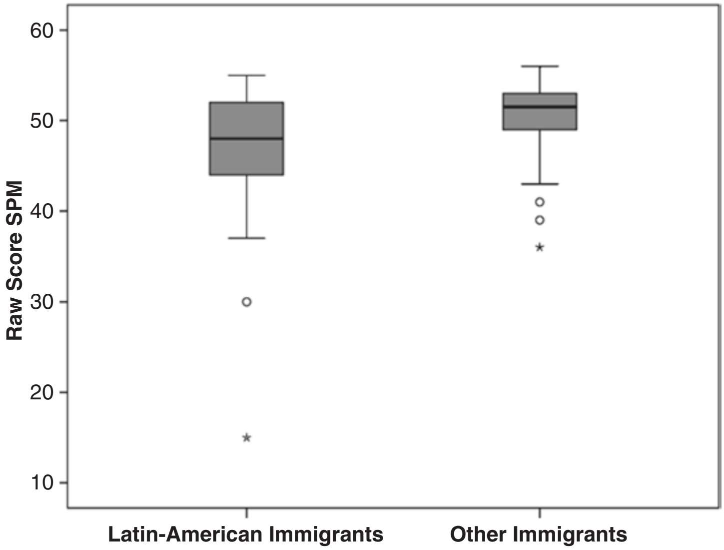


Fig. 6.7 Boxplot of the SPM scores for both groups of immigrants students

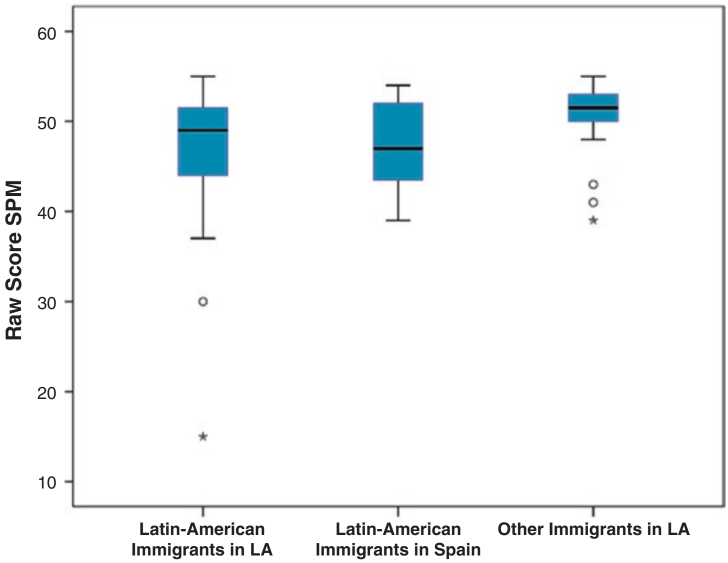


Fig. 6.8 Boxplot of the SPM scores for the three groups of immigrants students

A one-way between-groups analysis of variance (ANOVA) was conducted to explore the impact of immigrant groups on the SPM scores. There was a statistically significant difference at the $p < .05$ level in the SPM scores for the three immigrant groups [$F(2, 74) = 3.476$, $p = .036$]. The effect size, using η^2, was .085, which could be considered as a moderate effect size (Cohen, 1988). Post-hoc comparisons using the Bonferroni test indicated that the mean score for Group 3 ($M = 50.89$, $SD = 4.03$)

was significantly different from Group 1 (*M* = 45.89, SD = 9.67), but Group 3 was not significantly different from Group 2 (*M* = 47.56, SD = 4.69). Additionally, the means of Group 1 and Group 2 were not significantly different. Figure 6.8 shows the boxplot of SPM scores for the three immigrant groups.

When the outlier cases were deleted—which decreases the variability—almost the same results were found. The ANOVA indicated significant differences among groups [F(2, 69) = 7.681, *p* = .001]. Post-hoc comparisons using the Bonferroni test indicated that Group 3 (Mean = 51.83, SD = 1.9, *n* = 23) and Group 1 (Mean = 48.65, SD=4.6, *n* = 17) had significant differences at .048 level, and Group 1 and Group 2 (Mean = 47.56, SD = 4.69, *n* = 32) did not have significant differences. However, Group 2 and Group 3 had significant differences at .001 level. Note that the outlier cases were concentrated in Group 1 and Group 3.

Considering the three groups, significant differences were found regarding individual SES [F(2, 67) = 24.397, *p* = .000], school SES [F(2, 74) = 7.705, *p* = .001], and age [F(2, 74) = 7.843, *p* = .001]. Group 1 (Mean = 20.2, SD = 1.64) and Group 3 (Mean = 19.4, SD = 2.16) had higher individual SES than Group 2 (Mean = 16.5, SD = 1.85). No significant differences were found between Group 1 and 3. Regarding school SES, Group 1 and Group 3 were enrolled in higher SES schools (average = 2.48) than Group 2 (Mean = 2.06). No significant differences were found between Group 1 and 3. Regarding age, Group 2 was older (Mean = 15.1) than Group 1 (Mean = 14.6) and Group 3 (Mean = 14.5). No significant differences were found between Group 1 and 3 regarding age.

The results obtained, despite not being conclusive, were similar to other studies regarding cognitive performance differences between populations from developed and developing countries (te Nijenhuis et al., 2004) and, at least, they deserve more attention from Latin American researchers.

6.6 Parent Occupation and Cognitive Performance of Their Children

The relationship between parental occupation and the intelligence of their children has been investigated since early in the 20th century (Byrns & Henmon, 1936; Jordan, 1933; Canady, 1936). These first studies observed great variability and strong overlap between occupations. In general, children of professional parents had a higher mental ability than children of farmers or unskilled workers. However, the correlation between parental professional status and cognitive performance of children was low (<.30). Recent studies have not modified this picture and similar results have been published (Cheng & Furnham, 2014).

To our knowledge there are no Latin American studies on this subject. In our the SLATINT Project, 3368 out of 3572 Latin American students (i.e., excluding Latin American students studying in Spain, immigrants, and students aged 13 or 16 years old) provided information on the type of job of the principal provider of their families (65.4% of fathers were the principal provider). Table 6.10 shows the mean raw score for each type of job.

Table 6.10 Mean SPM score of Latin American students according to the job of the principal provider of family

Type of job	*n*	Mean	SD
Owner/trade or industry	366	45.6	6.9
Owner/service company	286	46.6	7.3
Owner/rural	27	43.7	7.0
Employee/trade or industry	461	44.8	7.4
Employee/service company	759	45.0	8.0
Employee/rural	39	42.0	7.9
Government employee	206	44.9	8.0
Military	27	43.8	10.5
Professional/Self-employed	222	47.0	6.8
Retired	76	44.2	7.8
Informal job	184	42.3	8.3
Other	715	43.8	8.3
Total	3368	44.8	7.8

The ANOVA indicated significant differences among groups of occupations [$F(11, 3356) = 6.281$, $p = .000$]. Post-hoc comparisons using the Bonferroni test indicated that the group of students whose parents were working in informal jobs had lower cognitive performance than students whose parents were working as owner/trade or industry, owner/service company, and professional/self-employed. Students whose parents were working as employee/rural had lower cognitive performance than students whose parents were working as owner/services companies or professional/self-employed. The rest of the occupational categories did not present significant differences. The occupational categories were placed into six broad groups according to their status: (1) Informal job; (2) Employee/Rural; (3) Government employee/Military; (4) Retired/Other; (5) Employee/Trade, Industry/Service Company, and (6) Owners/Trade, Industry/Service Company/Self-Employed, Professional. The Pearson correlation between occupational status and the SPM performance of children was low, but positive and statistically significant (.130, $p = .000$; same value for Spearman correlation).

6.7 Internet

Information available on the internet is diverse, and quantitatively huge. In this way, the search for information on the internet demands analysis, selection, and integration of information. It is inferred, therefore, that the use of the internet is related to the use of cognitive abilities. In our study, 3476 out of 3572 Latin American students (i.e., excluding Latin American students studying in Spain, immigrants, and students aged 13 or 16 years old) provided information about their access to the internet. From this total, 32.6% had no internet at home. Note that the SLATINT Project data was collected between 2007 and 2011. An independent-samples *t*-test was conducted

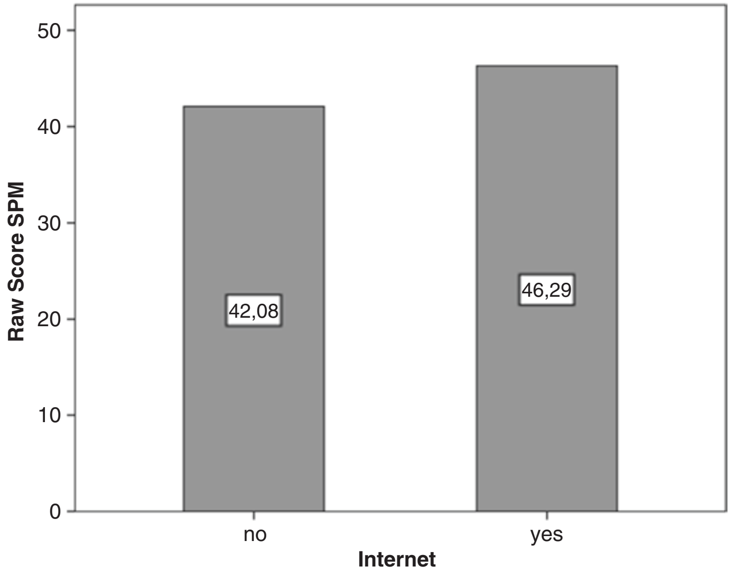


Fig. 6.9 Mean SPM score of students with and without internet at home

to compare the SPM performance of students who had internet at home (mean = 46.29, SD = 7.41, *n* = 2577) and those who did not (mean = 42.08, SD = 8.15, *n* = 1233). The mean differences, favoring the group with internet, were statistically significant [$t(3808) = 15.858$, $p = .000$]. The results are indicated in Fig. 6.9.

We performed the same analysis with PISA scores. We obtained the same results. Students with internet at home (Mean = 7.49, SD = 3.70) outperformed students without internet at home (Mean = 4.70, SD = 3.09). The mean differences were statistically significant [$t(3698) = 22.510$, $p = .000$].

The Spearman correlation between access to internet and cognitive performance on the SPM test was positive and statistically significant ($\rho = .272$, $p = .000$). However, after controlling for SES, partial correlation indicated no significant association between access to internet and cognitive performance.

6.8 Birth Order

Sibship size and its effect on cognitive performance of individuals has been a recurrent matter in social and behavioral research (Anastasi, 1956; Belmont, & Marolla, 1973; Downey, Powell, Steelman, & Pribesh, 1999; Downey, 2001). The most consistent result found is that individuals with fewer siblings have better cognitive performance compared to individuals from large families, and first-borns usually have higher IQs than children born later. The explanation would be that as the family increases, fewer resources are available and the quality of the intellectual environment declines. This hypothesis was termed Dilution of Resources (Downey, 2001).

Another complementary explanation (called the Confluence Model) is related to a confluence of factors that came together when families increase. These factors cause constant changes in the family's intellectual environment (Zajonc, 2001). For example, while there is no competition, first-borns receive more attention from their parents than later-born children. More attention means more exposure to adult language. As a family increases, first-borns assume the role of tutors for their younger siblings, which provides them with more cognitive activities. However, as a family increases, the linguistic maturity of the environment declines (e.g., a family with five or six children has a lower linguistic maturity than a family with three children), which would explain why children from small families have a higher cognitive performance compared to children from large families. On the other hand, Rodgers, Cleveland, van den Oord, and Rowe (2000) argued that the negative influence of sibship on intelligence was an illusion and presented several studies with no significant effect of birth order. According to these authors, there were methodological problems related to the time variation in the age of testing. Siblings (not twins) tested at the same time present developmental differences. These differences will be affected by the differences in the environment and by the "teaching function" (older siblings act as tutors for younger siblings). Until 11 years of age, environmental differences (disadvantages of increasing families) will have a negative effect; however, for older children, the teaching function will cancel out the first negative effect. Therefore, according to Rodgers et al, longitudinal studies (within families) do not indicate significant relationship between birth order and intelligence. The existence of birth-order differences would operate only between families (cross-sectional studies). Recently, Wänström and Wegmann (2017) studied a Swedish cohort of school children. They found a negative effect of sibship size on intelligence and on adult income, but not on school grades.

In our dataset, 3500 students provided information about their birth order. Table 6.11 and Fig. 6.10 shows a progressive decrease of the SPM scores as the order of birth increases for each age group (14 or 15 years old) and for the total sample. Several ANOVAs were conducted and significant differences among groups were found for the 14-year-old group [F(5, 3494) = 9.341, p = .000] and for the total sample [F(5, 3494) = 11.137, p = .000]. The six birth-order positions were divided in two groups: 1 (first- and second-birth positions) and 2 (last-birth positions). The T-test for independent groups indicated significant differences between the first positions (Group 1; mean = 45.4, SD = 7.7) and last positions (Group 2; mean = 43.3,

Table 6.11 Mean SPM score according to birth order

	14 years			15 years			Total		
Birth order	*n*	Mean	SD	*n*	Mean	SD	*n*	Mean	SD
1	973	45.5	7.4	604	45.4	8.0	1577	45.4	7.7
2	670	45.4	7.7	430	45.4	7.6	1100	45.4	7.7
3	303	43.8	7.8	184	43.6	8.1	487	43.7	8.0
4	124	43.1	7.5	78	43.9	8.3	202	43.4	7.8
5	42	40.5	10.0	26	42.7	9.8	68	41.3	9.9
6	42	40.5	10.0	24	43.2	6.8	66	41.5	9.0
Total	2154	44.9	7.8	1346	44.9	8.0	3500	44.9	7.9

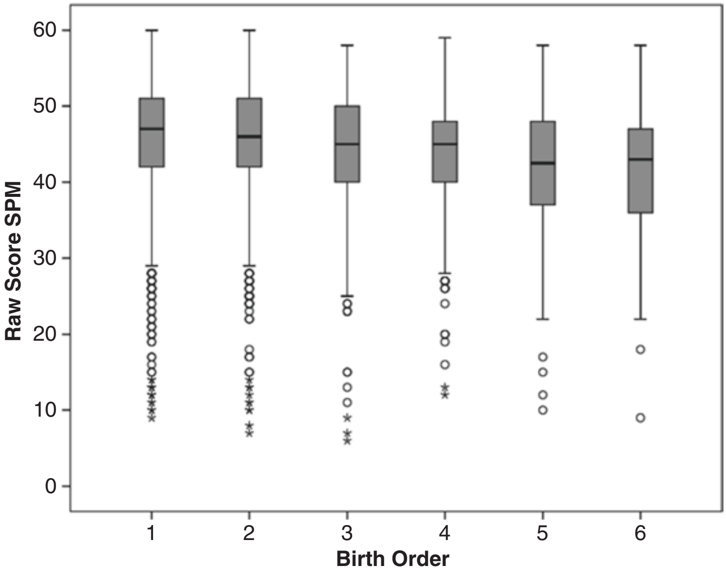


Fig. 6.10 Mean SPM score according to birth order

SD = 8.2) of the total sample [$t(3498) = 6.809$, $p = .000$). Similar results were found for age groups (14 and 15 years old). Note that there were no significant differences in the SPM scores between students aged 14 and 15 years. Even when the outliers were deleted, the pattern of differences remained the same.

The Spearman correlation between birth order and cognitive performance on the SPM test was negative and statistically significant ($\rho = -.106$, $p = .000$). A hierarchical regression was calculated to predict cognitive performance (SPM score) based on birth-order controlling SES effects. The results indicated that SES contributed significantly to the regression model [$F(13,227) = 456.791$, $p = .000$], and accounted for 12.4% of the variation in the SPM score. Introducing birth order explained an additional .04% of variation, and this change was significant [$F(13,226) = 14.048$, $p < .000$]. Therefore, in this case, the most important predictor was SES.

6.9 Human Capital in Latin America and Spain

In this section, we present comparisons between the performance of Spanish students and Latin American students to verify differences in the human capital available in developed and developing contexts. Once again, data from immigrant students studying in Latin America and Spain were eliminated from the analysis.

Our samples were assessed in the same period with the same instruments. This design rendered the study attractive. Nevertheless, it is worth remembering that the samples were not probabilistic (representative of countries). Therefore, some caution is recommended in using the results.

6.9.1 Intelligence

An independent-samples *t*-test comparing the SPM mean scores of the Latin American students and Spanish students (Table 6.12) found a significant difference between the means of the two groups [$t(3660) = -4.804$, $p = .000$]. The mean of the Latin American students was significantly lower ($M = 44.8$, SD = 7.9) than the mean of the Spanish students ($M = 48.9$, SD = 6.5). Differences were also observed in both sexes.

Additionally, it is possible to observe in Table 6.11 a mean IQ of 89 for the Latin American sample, and 97 for the Spanish sample, which are almost the same values estimated by Lynn and Vanhanen (2012), which were IQ 88 and IQ 98 for the Latin American countries (average of Argentina, Brazil, Chile, Colombia, Mexico, and Peru), and Spain, respectively. If 90 is the IQ breakpoint for a nation achieving reasonable development (Whetzel and McDaniel, 2006), the performance of our Latin American sample indicates that the region is close to achieving relative social well-being.

On the other hand, if 115 is the IQ breakpoint for achieving scientific-technological excellence Rindermann (2012), it would be interesting to verify the percentage of people with an IQ ≥ 115 in our samples. Accordingly, we extracted one factor from the PISA and the SPM scores (running principal axis factor extraction), and we converted the scores of this factor to a metric scale of IQ. There were 11.5% of Latin American students and 24.5% of Spanish students with an IQ ≥ 115.

6.9.2 School Achievement

The same tendency was found in the analysis of the PISA test. Latin American students had significantly lower performance than Spanish students (Table 6.13).

Table 6.12 Group differences (Latin American students × Spanish students) for the SPM test and estimated IQ

Measure		LA				Spain				
		n	Mean	SD	IQ	*n*	Mean	SD	IQ	*t*
SPM	F	1830	44.5	7.7	89	39	49.7	6.7	99	−4.158[a]
	M	1742	45.2	8.1	89	51	48.2	6.3	94	−2.690[a]
	Total	3572	44.8	7.9	89	90	48.9	6.5	97	−4.804[a]

[a]Sig. at $p < .000$

Table 6.13 Group differences (Latin American students × Spanish students) for the PISA test

Measure		LA			Spain			
		n	Mean	SD	*n*	Mean	SD	*t*
PISA	F	1804	6.3	3.6	39	8.4	3.4	−3.497[a]
	M	1687	6.9	3.9	52	8.4	3.9	−2.693[a]
	Total	3491	6.6	3.8	91	8.4	3.7	−4.441[a]

The correlation between the SPM and the PISA scores was .581 ($p = .000$) and .548 ($p = .000$) for the group of Latin American and Spanish students respectively
[a]Sig. at $p < .000$

Table 6.14 Percentage of students who correctly responded to the most difficut PISA items according to positions in *g*, SPM, and SES

Variables	Position	Hardest PISA items							
		1		9		16		5	
		LA	Spain	LA	Spain	LA	Spain	LA	Spain
g	Q1	5.9	22.2	3.3	11.1	15.5	22.2	12.9	0.0
	Q4	28.9	20.0	36.8	30.0	46.4	37.5	51.2	42.5
SPM	Q1	4.1	11.1	2.6	0.0	14.0	11.1	9.2	11.1
	Q4	19.8	17.4	30.1	39.1	40.0	34.8	43.0	34.8
SES	Low	4.4	4.8	5.1	19.0	15.8	28.6	13.8	23.8
	High	16.3	19.2	22.4	34.6	33.0	30.8	37.0	30.8

Note: *Q1* Quartile 1; *Q4* Quartile 4; *LA* Latin American students

6.9.3 Solving Problems

Solving problems (described in Chap. 4) is a human attribute that is well studied by the scientific community, and currently well appreciated by the new technological society. It is understood to be the ability to think in a flexible and creative way and is used to meet real-life challenges (OECD, 2016).

We surveyed the percentage of students from the highest and the lowest performance group in *g* and the SPM test that correctly responded to the most difficutl PISA problems (Table 6.14).

Table 6.14 shows that there were more Spanish students with the lowest cognitive performance that responded correctly to the most difficult PISA item test than the Latin American group. The reverse was also observed. There was a higher percentage of Latin American students from the higher cognitive group that correctly responded to the most difficult problems. Probably, this is the effect of educational inequality in the Latin American region. These results deserve further follow-up in future research. Regarding SES, there was a higher percentage of Spanish students from low SES that correctly responded to the hardest PISA problems. Regarding students from the high SES, the results were unclear.

6.10 Conclusion

We live in a fast-moving world, where developed countries drive the most important changes. This leads to developing countries moving rapidly to join the fast-moving world, especially in economy and technology. How prepared is the Latin America region to face these changes? According to the results of the SLATINT Project, samples of students from Argentina, Brazil, Chile, Colombia, Mexico, and Peru had lower performance than samples of students in Spain in reasoning (measured by the SPM test) and school achievement (measured by a short version of the PISA test), as expected from the literature. Moreover, the mean IQ calculated for the Latin

American samples were slightly higher than the IQs estimated by Lynn and Vanhanen (2002, 2006, 2012), but still within the expected range for the region. There is a strong association between reasoning and school performance. These factors are the core of the human capital of a nation. Therefore, policy-makers should know (and recognize) that raising the educational level of the population involves intervention on the intellectual level of the population.

References

Anastasi, A. (1956). Intelligence and family size. *Psychological Bulletin, 53*, 187–209.

Angelini, A. L., Alves, I. C. B., Custódio, E. M., Duarte, W. F., & Duarte, J. L. M. (1999). Padronização brasileira das matrizes progressivas coloridas de Raven. In J. C. Raven (Ed.), *Manual matrizes progressivas coloridas de Raven: Escala especial*. São Paulo: Centro Editor de Testes e Pesquisas em Psicologia.

Arias, W. L. (2014). Estilos de Aprendizaje e Inteligencia em Estudiantes Universitarios de Arequipa, Perú. *Revista de Estilos de Aprendizaje, 7*, 88–107.

Bandeira, D. R., Alves, I. C. B., Giacomel, A. E., & Lorenzatto, L. (2004). Matrizes progressivas coloridas de Raven—escala especial: normas para Porto Alegre, RS. *Psicologia em Estudo, 9*, 479–486.

Bandeira, D. R., Costa, A., & Arteche, A. (2012). The Flynn effect in Brazil: Examining generational changes in the Draw-a-Person and in the Raven's Coloured Progressive Matrices. *Revista Latinoamericana de Psicologia, 44*, 9–18.

Barber, N. (2005). Educational and ecological correlates of IQ: A cross-national investigation. *Intelligence, 33*, 273–284.

Becker, G. S. (1975). *Human capital: A theoretical and empirical analysis, with special reference to education* (2nd ed.). New York: Columbia University Press.

Belmont, L., & Marolla, F. A. (1973). Birth order, family size, and intelligence. *Science, 182*, 1096–1101.

Burhan, N. A. S., Razak, R. C., Salleh, F., & Tovar, M. E. L. (2017). The higher intelligence of the 'creative minority' provides the infrastructure for entrepreneurial innovation. *Intelligence, 65*, 93–106. https://doi.org/10.1016/j.intell.2017.09.007

Byrns, R., & Henmon, V. A. C. (1936). Parental occupation and mental ability. *Journal of Educational Psychology, 27*, 284–291. https://doi.org/10.1037/h0057697

Cheng, H., & Furnham, A. (2014). The associations between parental socio-economic conditions, childhood intelligence, adult personality traits, social status and mental well-being. *Social Indicators Research, 117*, 653–664. https://doi.org/10.1007/s11205-013-0364-1

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Hillsdale, NJ: Lawrence Earlbaum.

Colom, R., & Garcia-Lopez, O. (2002). Sex differences in fluid intelligence among high school graduates. *Personality and Individual Differences, 32*, 445–451.

Colom, R., Escorial, S., & Rebollo, I. (2004). Sex differences on the progressive matrices are influenced by sex differences on spatial ability. *Personality and Individual Differences, 37*, 1289–1293.

Dickerson, R. E. (2006). Exponential correlation of IQ and the wealth of nations. *Intelligence, 34*, 292–295.

Downey, D. B. (2001). Number of siblings and intellectual development. The resource dilution explanation. *American Psychologist, 56*, 497–504.

Downey, D. B., Powell, B., Steelman, L. C., & Pribesh, S. (1999). Much do about siblings: Change models, sibship size, and intellectual development. *American Sociological Review, 64*, 193–198.

Flores-Mendoza, C., Darley, M., & Fernandes, H. B. F. (2017). Cognitive sex differences in Brazil. *Mankind Quarterly, 57*, 34–51.

Flores-Mendoza, C., Widaman, K.F., Bacelar, T.D., & Lele, A.J. (2014). Propriedades psicométricas do Raven Geral no contexto de Minas Gerais. *Arquivos Brasileiros de Psicologia, 66*, 1–16.

Flores-Mendoza, C., Widaman, K. F., Mansur-Alves, M., Silva Filho, J. H., Pasian, S., & Schlottfeldt, C. G. M. (2012). Considerations about IQ and human capital in Brazil. *Temas em Psicologia (Ribeirão Preto), 20*, 133–154.

Flynn, J. R., & Rossi-Casé, L. (2012). IQ gains in Argentina between 1964 and 1998. *Intelligence, 40*, 145–150. https://doi.org/10.1016/j.intell.2012.01.006

Gelade, G. A. (2008a). IQ, cultural values, and the technological achievement of nations. *Intelligence, 36*, 711–718.

Gelade, G. A. (2008b). The geography of IQ. *Intelligence, 36*, 495−501.

Gunver, M. G., Senocak, M. S., & Vehid, S. (2017). To determine skewness, mean and deviation with a new approach on continuous data. *PONTE International Journal of Sciences and Research, 73*, 30–44.

Canady, H. G. (1936). The intelligence of Negro college students and parental occupation. *American Journal of Sociology, 42*, 388–389. https://doi.org/10.1086/217436

International Labour Office. (2017). *World employment and social outlook: trends 2017* (p. 2017). Geneva: ILO.

Instituto Nacional de Estadística e Informática – INEI (2015). Perú. Síntese Estadística 2015 [Statistical Overview 2015]. Lima: INEI. Retreved from https://www.inei.gob.pe/media/MenuRecursivo/publicaciones_digitales/Est/Lib1292/libro.pdf.

Jensen, A. R. (1998). *The g factor. The science of mental ability*. London: Praeger.

Jones, G., & Schneider, W. J. (2006). Intelligence, Human capital, and economic growth: a bayesian averaging of classical estimates (BACE) Approach. *Journal of Economic Growth, 11*, 71–93.

Jones, G., & Schneider, W. J. (2010). IQ in the production function. *Economic Inquiry, 48*, 743–755.

Jordan, A. M. (1933). Parental occupations and children's intelligence scores. *Journal of Applied Psychology, 17*, 103–119. dx.doi.org. https://doi.org/10.1037/h0071816

Kanazawa, S. (2006). IQ and the wealth of states. *Intelligence, 34*, 593–600.

Kanazawa, S. (2009a). IQ and the values of nations. *Journal of Biosocial Science, 41*, 537–556. https://doi.org/10.1017/S0021932009003368

Kanazawa, S. (2009b). Why liberals and atheists are more intelligent. *Social Psychology Quarterly, 73*, 33–57. https://doi.org/10.1177/0190272510361602

Lynn, R. (2006). *Race differences in intelligence. An evolutionary analysis*. Washington: Summit Publishers.

Lynn, R., & Mikk, J. (2007). National differences in intelligence and educational attainment. *Intelligence, 35*, 115–121.

Lynn, R. (2009). Fluid intelligence but not vocabulary has increased in Britain, 1979–2008. *Intelligence, 37*, 249–255.

Lynn, R. (2012). IQs predict differences in the technological development of nations from 1000 BC through 2000 AD. *Intelligence, 40*, 439–444. https://doi.org/10.1016/j.intell.2012.05.008

Lynn, R., & Meisenberg, G. (2010). National IQs calculated and validated for 108 nations. *Intelligence, 38*, 353–360.

Lynn, R., & Vanhanen, T. (2002). *IQ and the wealth of nations*. London: Praeger.

Lynn, R., & Vanhanen, T. (2006). *IQ and global inequality*. Washington, DC: Summit.

Lynn, R., & Vanhanen, T. (2012). National IQs: A review of their educational, cognitive, economic, political, demographic, sociological, epidemiological, geographic and climate correlates. *Intelligence, 40*, 226–234.

Lynn, R., Backhoff, E., & Contreras, L. A. (2005). Ethnic and racial differences on the standard progressive matrices in Mexico. *Journal of Biosocial Science, 37*, 107–113. https://doi.org/10.1017/S0021932003006497

Lynn, R., Harvey, J., & Nyborg, H. (2009). Average intelligence predicts atheism rates across 137 nations. *Intelligence, 37*, 11–15.

Lynn, R., Meisenberg, G., Mikk, J., & Williams, A. (2007). National IQs predict differences in scholastic achievement in 67 countries. *Journal of Biosocial Science, 39*, 861–874.

Mackintosh, N. J., & Bennett, E. S. (2005). What do Raven's matrice measure? An analysis in terms of sex differences. *Intelligence, 33*, 663–674. https://doi.org/10.1016/j.intell.2005.03.004

Marincovich, R. I., Sparosvich, E. F., Santana, M. C. D., Game, J. H., Gómez, C. C., & Marincovich, D. I. (2000). Estudio de la capacidad intelectual (Test de Matrices Progresivas de Raven) em escolares chilenos de 5 a 18 años. Antecedentes generales, normas y recomendaciones. *Revista de Psicología General y Aplicada, 53*, 5–30.

Millones, D. M., Flores-Mendoza, C., & Rivalles, R. M. (2015). Intelligence in Peru: Students' results in Raven and its relationship to SES. *Intelligence, 51*, 71–78.

Neisser, U., Boodoo, G., Bouchard Jr., T. J., Boykin, A. W., Brody, N., Ceci, S. J., … Urbina, S. (1996). Intelligence: Knowns and unknowns *American Psychologist*, 51, 77–101.

Nisbett, R. E., Aronson, J., Blair, C., Dickens, W., Flynn, J., Halpern, D. F., & Turkheimer, E. (2012). Intelligence. New Findings and Theoretical Developments. *American Psychologist, 67*, 130–159. https://doi.org/10.1037/a0026699

Nista, M. T. F., & Ibarra, S. M. M. (2014). Datos Normativos de las Matrices Progresivas Coloreadas em niños indígenas yaquis. *Anuario de Psicologia, 44*, 373–385.

Obydenkova, A. V., & Salahodjaev, R. (2017). Government size, intelligence and life satisfaction. *Intelligence, 61*, 85–91. https://doi.org/10.1016/j.intell.2017.01.008

OECD. (2016). *The survey of adult skills: reader's companion*, *Oecd skills studies* (2nd ed.). Paris: OECD. https://doi.org/10.1787/9789264258075-en

Quiroz, R., Chávez, W., & Holgado, M. (1998). Baremos para la escala especial de las Matrices Progesivas de J.C. Raven en niños de educación primaria de la ciudad del Cusco. *SITUA*, Año VI, 11. Retrieved from http://sisbib.unmsm.edu.pe/bvrevistas/situa/1998_n11/baremos.htm#.

Raven, J., Raven, J. C., & Court, J. H. (2000). *Manual for Raven's progressive matrices and vocabulary scales. Section 3: The standard progressive matrices*. Oxford, England: Oxford Psychologists Press.

Reeve, C. L. (2009). Expanding the g-nexus: Further evidence regarding the relations among national IQ, religiosity and national health outcome. *Intelligence, 37*, 495–505.

Rindermann, H., & te Nijenhuis, J. (2012). Intelligence in Bali—A case study on estimating mean IQ for a population using various corrections based on theory and empirical findings. *Intelligence, 40*, 395–400. https://doi.org/10.1016/j.intell.2012.06.005

Rindermann, H. (2007). The g-factor of international cognitive ability comparisons: the homogeneity of results in PISA, TIMSS, PIRLS and IQ-tests across nations. *European Journal of Personality, 21*, 667–706.

Rindermann, H. (2012). Intellectual classes, technological progress and economic development: The rise of cognitive capitalism. *Personality and Individual Differences, 53*, 108–113. https://doi.org/10.1016/j.paid.2011.07.001

Rushton, J.P., & Čvorovic, J. (2009). Data on the raven's standard progressive matrices from four serbian samples. *Personality and Individual Differences, 46*, 483–486.

Rindermann, H., & Meisenberg, G. (2009). Relevance of education and intelligence at the national level for health: The case of HIV and AIDS. *Intelligence, 37*, 383–395.

Rindermann, H., & Thompson, J. (2011). Cognitive capitalism: The effect of cognitive ability on wealth, as mediated through scientific achievement and economic freedom. *Psychological Science, 22*, 754–763.

Rodgers, J. L., Cleveland, H. H., van den Oord, E., & Rowe, D. C. (2000). Resolving the debate over birth order, family size, and intelligence. *American Psychologist*, 55, 599—61.

Rushton, J. P., & Templer, D. I. (2009). National differences in intelligence, crime, income, and skin color. *Intelligence, 37*, 341–346.

Salahodjaev, R., & Azam, S. (2015). IQ and the weight of nations. *Personality and Individual Differences, 87*, 105–109. https://doi.org/10.1016/j.paid.2015.07.033

Salahodjaev, R. (2016). Intelligence and deforestation: International data. *Forest Policy and Economics, 63*, 20–27. https://doi.org/10.1016/j.forpol.2015.12.003

Schultz, T. W. (1971). *Investment in human capital: The role of education and of research*. New York: Free Press.

Schweizer, K., Goldhammer, F., Rauch, W., & Moosbrugger, H. (2007). On the validity of Raven's matrices test: Does spatial ability contribute to performance? *Personality and Individual Differences, 43*, 1998–2010. https://doi.org/10.1016/j.paid.2007.06.008

Shatz, S. M. (2008). State IQ and fertility in the United States. *Mankind Quarterly, 49*, 38–49.

Stolarski, M., Jasielska, D., & Zajenkowski, M. (2015). Are all smart nations happier? Country aggregate IQ predicts happiness, but the relationship is moderated by individualism–collectivism. *Intelligence, 50*, 153–158. https://doi.org/10.1016/j.intell.2015.04.003

te Nijenhuis, J., de Jong, M., Evers, A., & van der Flier, H. (2004). Are cognitive differences between immigrant and majority groups diminishing? *European Journal of Personality, 18*, 405–434. https://doi.org/10.1002/per.511

te Nijenhuis, J., Tolboom, E., Resing, W., & Bleichrodt, N. (2004). Does cultural background influence the intellectual performance of children from immigrant groups? *European Journal of Psychological Assessment*, 20, 10-26. Doi: https://doi.org/10.1027//1015-5759.20.1.10.

te Nijenhuis, J., Willigers, D., Dragt, J., & van der Filer, H. (2016). The effects of language bias and cultural bias estimated using the method of correlated vectors on a large database of IQ comparisons between native Dutch and ethnic minority immigrants from non-Western countries. *Intelligence, 54*, 117–135.

Van der Ven, A. H. G. S., & Ellis, J. L. (2000). A Rasch analysis of Raven's standard progressive matrices. *Personality and Individual Differences, 29*, 45–64. https://doi.org/10.1016/S0191-8869(99)00177-4

Vásquez, A. D. (2014). Estudio Psicométrico del test de Matrices Progresivas de Raven a Colores en estudiantes de primaria de Lima Metropolitana. *Revista de Investigación em Psiologia, 5*, 43–54.

Vittorio, D., & Ostuni, N. (2013). The burden of disease and the IQ of nations. *Intelligence, 28*, 109–118. https://doi.org/10.1016/j.lindif.2013.09.015

Wai, J., Lubinski, D., & Benbow, C. P. (2009). Spatial ability for STEM domains: Aligning over 50 years of cumulative psychological knowledge solidifies its importance. *Journal of Educational Psychology, 101*, 817–835. https://doi.org/10.1037/a0016127

Wänström, L., & Wegmann, B. (2017). Effect of sibship size on intelligence, school performance and adult income: Some evidence from Swedish data. *Intelligence, 62*, 1–11. https://doi.org/10.1016/j.intell.2017.01.004

Whetzel, D. L., & McDaniel, M. A. (2006). Prediction of national wealth. *Intelligence, 4*, 449–458.

Wicherts, J.M. (2009). The impact of papers published in Intelligence 1977-2007 and an overview of the citation classics. *Intelligence, 37*, 443–446.

Wicherts, J. M., Dolan, C. V., & van der Maas, H. L. J. (2010). The dangers of unsystematic selection methods and the representativeness of 46 samples of African test-takers. *Intelligence, 38*, 30–37.

World Economic Forum—WEF (2015). *The Human Capital Report*.

World Economic Forum—WEF (2016). *The future of jobs. Employment, skills, and workforce strategy for the fourth industrial revolution*.

Zajonc, R. B. (2001). The family dynamics of intellectual development. *American Psychologist, 56*, 490–496.

Chapter 7
Final Words

Abstract The previous chapters discussed and summarized the structure of intelligence, effect of education, influence of socioeconomic status of school and students, cognitive sex differences, creativity, and human capital available in the Latin America region. Three strategies are suggested for the Latin American region to meet the challenges of the Fourth Industrial Revolution: (1) increase the national average intelligence, (2) improve school environments, and (3) preserve the available smart fraction.

When this book was written, most of the Latin American countries, especially the southern countries, had improved from an average level of human development to a high level. However, in spite of the improvement of the social indices (except for Venezuela, a pitiful exception with an 87% poverty rate at the end of 2017), the social and economic inequality within the countries is the highest in the world. At the same time, citizens of Latin American countries have developed a better awareness of the education effect and now take an active part in the advancement of technologies, and have a better understanding of the crucial role of education in the reduction of inequality.

After a decade and a half, the Latin American society should be satisfied with the fulfillment of the agreements signed in 2000 during the World Education Forum in Dakar, Senegal (an agreement known as the Dakar Framework for Action) and sponsored by UNESCO. By 2015 (deadline for achieving all goals), the region's countries were close to achieving a universal primary school attendance (95%); more than half of all young people (60%) had completed secondary education, and 30% (growing) of young adults were enrolled in tertiary education (i.e., university). However, one of the goals (perhaps the factor most related to human capital) could not be reached. This goal is quality of education. All international assessments sponsored by the OECD (Organisation for Economic Co-operation and Development), such as the PISA test, indicated that the performance of Latin American students is the lowest among the participating countries (except for Chile).

"Learning crisis," instead of "education crisis," is the new warning of international organizations such as the World Bank or UNESCO. Despite free access to

C. Flores-Mendoza et al., *Intelligence Measurement and School Performance in Latin America*, https://doi.org/10.1007/978-3-319-89975-6_7

school, international assessment results indicate that young people from developing countries do not absorb the basic knowledge in mathematics and reading that can help them complete secondary education. According to the report of the World Bank (2018), three-quarters of grade 3 students from Kenya, Tanzania, and Uganda could not read the sentence "The name of the dog is Puppy." Half of the sampled grade 5 students from rural India could not solve the subtraction equation 46–17. Regarding Latin America, if the current rate of improvement of Brazilian students remains the same, they will reach the average score in mathematics of developed countries in 75 years (at least), or 260 years in the case of reading. Additionally, PISA test-takers at the 75th percentile from Brazil, Colombia, Costa Rica, and Peru performed below the 25th percentile of the OECD average. Moreover, top Latin American students did not achieve the performance of students from Korea, Japan, or Singapore who were at the bottom quarter (25th percentile). These data present a terrible scenario.

The current priority of governments is to improve learning. However, where should they start? What is known about the factors that drive students' performance in Latin America? We attempted to answer this question by presenting the results of our project entitled Study of the Latin American Intelligence (SLATINT). This project was based on 120 years of differential psychology research. Differential psychology is the largest division of psychological science, but it is unfortunately ignored by education policies. The results obtained by the SLATINT Project were robust. The most important factor, but not the only one, to explain differences in school performance is intelligence.

However, what is intelligence? There is probably no universally-accepted concept of intelligence. Nevertheless, the observation that different tasks correlated positively indicated to us that intelligence can be a general ability and this supports the differential psychology theorem that has shown us the same trend since the beginning of the twentieth century.

We observed a slight influence of the socioeconomic status (SES) of schools on the performance in visuo-spatial reasoning tests such as the Matrices Progressive of Raven (SPM)) or the Inductive Reasoning test (IR). However, no significant influence by either the SES of students or the SES of schools on general intelligence (*g* factor) was observed. On the other hand, there was significant influence of school SES, and not the SES of students, on school performance, which was measured by a short version of the PISA test. More importantly, this influence remained even after controlling for the intelligence variable. In general, these results (described in Chap. 3) indicated that despite the strong correlation between intelligence and school performance, the improved school environment (i.e., school SES) affected the results differently. A moderate effect on school performance, but no significant effect on intelligence, was observed. This is the reason why intelligence cannot be confused with school performance as these are different.

As previously mentioned, intelligence is important for school performance. However, it is not sufficient. In Chap. 4, we reported that 51.4% of the SLATINT sample with high cognitive functioning was able to correctly calculate the mean of a set of five values. For a separate group of students with high cognitive functioning (high "*g*") according to the SES of their school (low and high), we found that 45.5%

of the students enrolled in high SES schools responded correctly to the hardest PISA questions compared to 13% of students enrolled in low SES schools. In this case, it was clear that the problem was not related to differences in intelligence. The problem was related to the SES differences of schools. Note that we do not know if Latin American schools of high SES have the same environmental quality as schools from countries with high school performance; probably not if PISA-OECD results are considered. However, we know about differences in cognitive performance.

Creativity at the potential level (not at achievement level) was related to intelligence only in groups with low cognitive performance, which gave support to the Threshold Hypothesis (i.e., creativity is part of the cognitive system up to a certain level). However, the relationship decreased after sex differences and school SES were included in the analysis. The school SES variable was the most important predictor of potential creativity, at least in our study. If these results were robust and reliable, the message would be that schools with a good environment also benefit the creativity of the students.

In Chap. 5, the polemic issue of cognitive sex differences was scrutinized. Seven of our studies were presented, and intelligence was analyzed at the specific and latent level (or *g* factor), in samples of both children and adults. Our results indicated no cognitive sex differences in childhood, but consistent differences were found in adulthood. These differences were statistically significant at the specific level (e.g., visuo-spatial reasoning favoring males or perceptual speed favoring females). The size effect (using *Cohen-d* classification) varied from small (mental folding favoring females) to medium (numerical speed favoring males). Additionally, there was over-representation of males in the upper tail of the distribution for spatial reasoning abilities (measured by the APM test), which supported the greater male variability hypothesis. If STEM disciplines/jobs demand specific abilities such as visuo-spatial ability, the under-representation of females in these positions (currently 30%) is unsurprising. Nevertheless, it would be interesting to monitor over time if government policies dedicated to gender equity in science and technology brought about a reduction of sex differences in visuo-spatial skills.

Sex differences in general ability (or *g* factor) are a different story. Our SLATINT Project indicated differences (favoring males) equivalent to 3.6 IQ points, a value similar to the results found in another study (Flores-Mendoza et al., 2013). Additionally, this difference is the same value proposed by several differential psychologists (Lynn, 1999; Lynn & Irwing, 2004; Nyborg, 2003). Nevertheless, despite the significant p-value, these differences between males and females in *g* were equivalent to a negligible effect size. Thus, our results replicated another scientists' results (Colom, Juan-Espinosa, Abad, & García, 2000; van der Sluis et al., 2006), which asserted nil sex differences in general intelligence.

Finally, in Chap. 6 we analyzed the human capital available in Latin America based on the cognitive performance of our samples. We used the same method used in international studies to calculate the IQ of nations. The results indicated a mean IQ for Latin American samples slightly higher than that estimated by Lynn and Vanhanen (2006, 2012), but all of them lower than the average IQ of Spanish students.

Previously, we said that the equivalence between high-SES Latin American schools and the schools in countries with high school performance was unknown. We assumed that social equivalence does not exist if we consider that the top Latin American students performed below the 25th percentile of PISA test-takers from developed countries. If the results of cognitive performance obtained by the SLATINT Project were reliable, it is reasonable to infer that, beside differences in the quality of schools, national cognitive differences follow school performance differences between countries. In Chap. 3, our results indicated that cognitive differences were the strongest predictor of school performance.

Is it possible to increase intelligence? There is considerable research on this topic. Unfortunately, only cognitive training studies were successful in raising IQ points. The effect is maintained while the training is in progress. Afterwards, the effect decreases. In contrast, several well-conducted studies have demonstrated that intelligence test scores are very stable over a life span (Deary, 2014; Gow et al., 2011). The reader must remember that according to our results, schools with good environments (high SES) had a higher effect on school performance than for intelligence. More evidence about the difficulty in changing intelligence was related to immigration. We found that the cognitive performance of immigrant students studying in the Latin American region was not significantly different from the performance of Latin American immigrant students studying in Spain. It was a surprising result. We are conscious that our sample of immigrant students was small, but we consider that at least the study deserves to be replicated. In any case, improving intelligence is still the Rosetta stone in behavioral science.

Would a mean IQ of 89 estimated for the Latin America region be enough for dealing with the challenges of the Fourth Industrial Revolution? It is not easy to respond to this question. Brazil, despite its mean IQ of 86 or 87, exported more high-technology in 2016 (US$ 9,775,328.34) than Argentina (US$ 1,300,925.70), Chile (US$ 620,263.60), or Peru (US$ 162,740.32), and was closer to Denmark (US$ 9,302,857.75) and Israel (US$ 10,278,901.00),[1] countries with mean IQs estimated at 98 and 95, respectively, by Lynn and Vanhanen (2006). Perhaps it would be more useful to verify the proportion of smart people available in the region. In our dataset, we detected 16.1% of Latin American students (10.8% Brazil) and 33.6% of Spanish students with an IQ $\geq$ 115 based only on the SPM test. If scores were based on the SPM and the PISA test, we obtained 11.5% (9.7% Brazil) of Latin American students and 24.5% of Spanish students with an IQ $\geq$ 115. Note that an IQ $\geq$ 115 is the threshold for achievement of scientific-technological excellence. Therefore there is a smaller proportion of intelligent people in the Latin American region than in Spain. So, what is the factor that allows Brazil to export high technology at the same rate as Denmark?

Flores-Mendoza et al. (2012) studied the human capital in Brazil. The authors asserted that the cognitive performance of the top human capital, which was concentrated in Brazilian public universities, was at the same level as the performance of the samples of students from developed countries. Note that Brazil has around

[1] Data according the World Bank (https://data.worldbank.org/indicator/TX.VAL.TECH.CD).

2400 universities, but only 12% are public institutions of higher education. Considering that public institutions select their applicants through rigorous entrance exams, the study of Flores-Mendoza et al. estimated that around 60% of top students who completed secondary school were absorbed by public universities in 2008. What is the quality of these Brazilian (public) universities that causes them to absorb most of the top students? According to QS World University Ranking, two Brazilian universities (University of São Paulo and University of Campinas) are among the 200 top universities in the world. It is worth noting that 90% of Brazilian scientific production (papers) are produced by public universities. The message offered in the study of Flores-Mendoza et al. for Brazil could be extended to the Latin American region. By preserving the smart fraction, i.e., preventing "brain drain" through investment in centers of excellence for higher education, the region could achieve great productivity in all areas.

Smart fraction is necessary for scientific and technological production; however, the well-being of a nation and reduction of inequality are more dependent on the average school and cognitive performance. There are studies pointing out that social skills are also increasingly demanding interest by the labor market (Deming, 2017). However, we prefer to be cautious. Using the words of the World Bank, there is a "learning crisis." National well-being, which includes economics, work and health dimensions, in a population without reasonable skills in solving problems, seems utopic.

While it is true that it is not simple to increase intelligence, at least through specific cognitive training, there is evidence of an increase in average performance on intelligence tests from generation to generation (a phenomenon called the Flynn effect). Behavioral science does not know what aspects of the environment contribute to this increase over time. Regarding the present study, the results indicated that improved environments are associated positively with better school performance, regardless of the student's socioeconomic status. This improved school performance perhaps drives intelligence over time, by having generations of fathers and mothers that are more educated than their parents.

We hope that this study can be replicated by a new generation of Latin American researchers (see complementary statistical information in the Addendum). We are convinced that by tracking individual differences in intelligence and its relation to school performance, we are tracing the region's possibilities to develop.

References

Colom, R., Juan-Espinosa, M., Abad, F., & García, L. F. (2000). Negligible sex differences in general intelligence. *Intelligence, 28*, 57–68. https://doi.org/10.1016/S0160-2896(99)00035-5

Deary, I. (2014). The stability of intelligence from childhood to old age. *Current Directions in Psychological Science, 23*, 239–245. https://doi.org/10.1177/0963772141453695

Deming, D. J. (2017). The growing importance of social skills in the labor market. *The Quarterly Journal of Economics, 132*, 1593–1640. https://doi.org/10.1093/qje/qjx022

Flores-Mendoza, C., Widaman, K. F., Mansur-Alves, M., Silva Filho, J. H., Pasian, S., & Schlottfeldt, C. G. M. (2012). Considerations about IQ and human capital in Brazil. *Temas em Psicologia (Ribeirão Preto), 20*, 133–154.

Flores-Mendoza, C., Widaman, K. F., Rinderman, H., Primi, R., Mansur-Alves, M., & Pena, C. C. (2013). Cognitive sex differences in reasoning tasks: Evidence from Brazilian samples of educational settings. *Intelligence, 41*, 70–84.

Gow, A. J., Johson, W., Pattie, A., Brett, C. E., Beverly, R., Starr, J. M., & Deary, I. J. (2011). Stability and change in intelligence from age 11 to ages 70, 79, and 87: The Lothian birth cohorts of 1921 and 1936. *Psychology and Aging, 26*, 232–240. https://doi.org/10.1037/a0021072

Lynn, R. (1999). Sex difference in intelligence and brain size: A developmental theory. *Intelligence, 27*, 1–12.

Lynn, R., & Irwing, P. (2004). Sex differences on the progressive matrices: A metaanalysis. *Intelligence, 32*, 481–498.

Lynn, R., & Vanhanen, T. (2006). *IQ and global inequality*. Washington, DC: Summit.

Lynn, R., & Vanhanen, T. (2012). National IQs: A review of their educational, cognitive, economic, political, demographic, sociological, epidemiological, geographic and climate correlates. *Intelligence, 40*, 226–234.

Nyborg, H. (2003). Sex differences in g [chapter 10]. In H. Nyborg (Ed.), *The scientific study of general intelligence: Tribute to Arthur R. Jensen*. Oxford: Pergamon.

Van der Sluis, S., Posthuma, D., Dolan, C. V., de Geus, E. J. C., Colom, R., & Boomsma, D. I. (2006). Sex differences on the Dutch WAIS-III. *Intelligence, 34*, 273–289. https://doi.org/10.1016/j.intell.2005.08.002

World Bank. (2018). *World Development 2018: Learning to Realize Education's Promise*. Washington, DC: World Bank. https://doi.org/10.1596/978-1-4648-1096-1

Appendix: Complementary Data

Descriptive statistics, according to SES, for the SPM test administered to the six Latin American samples

	SPM (Low SES)			SPM (Middle SES)			SPM (High SES)		
Samples	*n*	M	SD	*n*	M	SD	*n*	M	SD
Rosario	162	40.6	9.04	171	45.6	6.09	169	47.3	6.23
Belo Horizonte	239	40.4	8.94	175	41.3	8.58	229	47.3	6.53
Santiago	184	42.8	7.44	139	44.6	8.02	212	48.7	6.11
Bogotá	195	41.9	6.61	190	42.9	6.27	229	44.3	7.33
Mexico City	227	43.9	6.94	208	48.2	5.90	186	48.9	4.97
Lima	238	44.5	8.51	158	48.3	6.80	248	50.0	5.89
Total	1245	42.4	8.12	1041	45.18	7.41	1273	47.8	6.52

Note: *SPM* standard progressive matrices of Raven; *SES* Socioeconomic status of student (education mother, TV cable, MP3 player, phone, computer, Internet, video game, weekend magazine). Period of assessment: 2007–2011 (70% between 2008 and 2009)

Percentile	Rosario	Belo Horizonte	Santiago	Bogotá	Mexico City	Lima
5	28	27	32	31	34	35
10	35	31	36	35	38	39
15	37	34	39	36	40	41
20	39	36	40	38	41	42
25	40	38	41	39	42	43
30	41	40	42	40	43	44
35	42	41	43	41	44	45
40	43	42	44	42	45	46
45	44	43	45	43	46	47
50	45	44	46	44	47	48
55	46	45	47	45	48	49
60	47	46	48	45	49	50

C. Flores-Mendoza et al., *Intelligence Measurement and School Performance in Latin America*, https://doi.org/10.1007/978-3-319-89975-6

Percentile	Rosario	Belo Horizonte	Santiago	Bogotá	Mexico City	Lima
65	48	47	49	46	50	51
70	49	48	50	47	51	52
75	50	49	51	48	52	53
80	51	50	52	49	53	54
85	52	51	53	50	54	55
90	53	52	54	51	55	56
95	54	54	56	53	56	57
99	57	57	58	56	57	58
N	552	640	511	646	649	574
Mean	44	43	46	43	47	48
SD	8.7	8.8	7.6	6.8	6.6	7.3
Assessment year	2009	2007–2008	2008	2008	2007–2008	2007–2011
Mean age (SD)	14.5 (0.50)	14.4 (0.48)	14.1 (0.35)	14.4 (0.48)	14.4 (0.48)	14.5 (0.50)
n° Public schools	7	10	1	3	3	3
n° Private schools	5	3	5[a]	9	6	7
School Grade	9	8	9	9	9	9
Females	50.9%	54.1%	47.5%	53.7%	50.8%	48.9%

Standard Progressive Matrices of Raven
Smoothed Norms for Latin American samples
Data collected in the period 2007–2011 (70% between 2008 and 2009)
[a]A school was mixed (private/public)

Index

A
Advanced Progressive Matrices (APM), 44, 46, 66, 68, 72, 84
Analysis of variance (ANOVA), 90

B
Bonferroni test, 101–103
Brazilian Cognitive Reasoning Battery, 65
Brazilian Ministry of Education, 5
Brazilian National Council for Scientific and Technological Development, 8

C
Categorical Principal Components Analysis (CATPCA), 46
Cognitive and processing-information models, 9
Cognitive sex differences
  behavioral science, 75
  Danish society, 63
  developmental theory, 69–71
  EUA-Europe axis, 64
  at g level, 73–74
  in Latin American samples, 71
  males and females, 64
  multivariate analysis, 73
  non-cognitive factors, 75
  Personality and Individual Differences, 63
  scientific study, 63
  in univariate analysis, 71–73
  variability hypothesis
    general intelligence, 64
    in Latin American studies, 65–68
    males and females, 64
    SLATINT Project, 67–70
    STEM, 64
  verbal ability tests, 75
Colored Progressive Matrices (CPM), 44, 71, 96
Complex Problem Solving, (CPS), 44
Confluence Model, 105
Correlations matrices
  Argentina sample, 18
  Brazilian sample, 18
  Chilean sample, 19
  Colombian sample, 19
  Latin American sample, 20
  Mexican sample, 19
  Peruvian sample, 20
  Spaniard sample, 20
Creativity
  “Big-C” and “little-c”, 57
  bivariate correlations, 58
  British Turner Prize-winning painter, 56
  Chris Ofile’s art, 56
  cognitive assessment session, 56
  components, 57
  correlation, and intelligence, 58
  CV1 and CF2, 58
  “divergent thinking”, 57
  explanatory and predicted variable, 58
  expression, 57
  figurative, 59
  general instruction, 57
  intelligence, 59
  metric scale of IQ, 58
  psychology researchers, 56
  Threshold Hypothesis, 58
  Torrance Test of Creative Thinking, 57
Cronbach’s alpha, 46, 50

C. Flores-Mendoza et al., *Intelligence Measurement and School Performance in Latin America*, https://doi.org/10.1007/978-3-319-89975-6

D
Differential Aptitude Tests (DAT), 72
Draw-a-Man-Test (DMT), 72
Draw-a-Person Test, 83

E
EQS 6.1 software, 18

F
Flynn Effect, 94

G
General cognitive ability, 83
General intelligence, 15, 21, 22
General model of intelligence (*g* factor)
  adults, 15
  challenge, 15
  cognitive measures, 15–17
  correlations matrices, 17–20
  exploratory factor analysis, 21
  hierarchical model, 14
  indicator indifference principle, 13
  individual countries, 22
  individual samples, 21–22
  IQ tests, 14
  Latin-American sample, 21, 22
  mental activity, 13
  orthogonal methods, 14
  psychological measurement, 15
  robust statistical techniques, 22
  SEM modeling, 18
  SLATINT project, 15
  transformation and indeterminateness, 13
  Triarchic Theory of Intelligence, 15
Gross Domestic Product (GDP), 86

H
Human capital (HC)
  economic activity, 80
  human right principles, 80
  in Latin American and Spain
    "Greenwich-IQ", 85, 93–98
    developed and developing contexts, 106
    intelligence, 107
    school achievement, 107–108
    solving problems, 108
    SPM test, 90–93
  industrial revolution, 80
  international institutions, 80
  IQ of nations, 85
  non-human capital, 80
  physical abilities, 80
  skills and knowledge, 80
  wealth of nations, jobs and distribution, 80–83
Human Development Index (HDI), 2

I
Immigrants, 99–102
Inductive Reasoning test (IR), 114
Intelligence
  artificial, 26, 79
  cognitive computing/augmented, 79
  cultural influences, 99
  and education, 26–39
  group differences, 107
  human, 83
  independent-samples *t*-test, 107
  mean IQ, 107
  national IQ, 83–87
  parental occupation, 102
  PISA and SPM scores, 107
  sibship, 105
IQ
  cognitive national achievement, 90
  estimation, 83
  "Greenwich-IQ", 93–98
  national differences, 86
  and notable social variables, 86
  and social variables, 86
  and SPM test, 107
IQ and the Wealth of Nations, 3
Item characteristic curve (ICC), 47, 51, 92
Item Response Theory (IRT), 92

L
Lagrange multiplier tests, 21
Latin America region
  Brazilian students, 114
  education effect, 113
  IQ, 115, 116
  SLATINT, 114
Latin American people
  in univariate analysis, 71–73
  multivariate analysis, 73
  variability hypothesis, 65–68
Latin American samples, 15, 18, 20, 21
Levene's Test of Equality of Error Variance, 74
Life outcomes
  psychological tests, 3

Linear regression
g score—Final model, 37
PISA score – Final model, 38

M
Matrices Progressive of Raven (SPM), 114
Multiple Intelligence Model, 15

O
Organisation for Economic Co-operation and Development (OECD), 59, 80
large-scale test, 2

P
PISA score
boxplot, 30
cognitive performance, 29
complexity, 27, 28
g score, 36, 38, 39
histogram and normal Q-Q plot, 37
linear regression, 38
SES of students, 38
vs. SPM scores, 30
statistics, 35
PISA test, school knowledge, 59
Policy makers in education, 39
Problem solving
ability level, 45
algorithms, 44
categorical principal component analysis, 50
CFA, 51
cognitive processing, 46
cognitive psychologist, 43
CPM and APM tests, 44
CPS, 44
CTT, 51
disagreement, 52
error type and wrong alternative answer, 53
human behavior research, 43
ICC, 51
in intelligence tests, 44
incomplete correlate error, 53
individuals with autism, 45
Latin American students, 50
methods, 43
PISA items, 46
prototypical problem, SPM test, 45
psychometricians, 43
SPM items, 52
strategies, 44
students of low performance, 53
the *g* factor, 46–50
Type II, III, and IV errors, 56
wrong alternative answer, 52
wrong answer alternatives, 54, 55
wrong principle error, 53
Programme for International Student Assessment (PISA) Test, 2
Progressive Matrices of Raven tests, 93

Q
Q-Q plot
g score, 36
PISA standardized score, 37

R
Raven's Colored Progressive Matrices CPM), 72

S
School performance
cognitive, 27
intelligence, 27, 114
Latin American students, 29
PISA, 115
in schools and teachers, 28
SES, 114
SES Latin-American schools, 116
SLATINT project, 114
Science, Technology, Engineering/ Mathematics (STEM), 64
SES
sex and school, 60
SLATINT Project, 15, 27, 29–38
Latin American people, 87
public schools, 87
samples and quality, 88–90
sampling criteria, 87
school samples, 87
SES level, 87
Socioeconomic status (SES)
Argentine schools, 32
general intelligence, 114
vs. g score, 35
high and low schools, 29, 36
individual, 6, 7
individual (students) and group (school) levels, 31
intelligence, 29
Latin-American schools, 116
measurement, 31
mother's education level, 30

Socioeconomic status (SES) (*cont.*)
nonparametric Spearman correlation, 35
PISA score distribution, 30
schools, 6, 31, 38, 115
SPM score distribution, 30
student per country, 33
students, 6, 7, 31, 38
Specific abilities, sex differences
in univariate analysis, 71–73
multivariate analysis, 73
SPM score
birth order, 105
and CPM, 96
factors, 90
Latin American students, 103
students with internet at home, 104
Standard Progressive Matrices (SPM), 44–46, 49–52, 55, 58, 59, 72, 90
boxplot, 30
group of students, 27
PISA results, 29
Structural Equation Modeling (SEM), 18, 22
Study of the Latin American Intelligence (SLATINT) project
behavioral science, 117
Brazilian public universities, 116, 117
Brazilian students, 114
budget constraints, 5
double-check translation, 5
human capital, 9, 115
individual differences, 117
international organizations, 113
IQ estimation, 116
Latin American immigrant students, 116
Latin-America region, 1–4
Latin-American students, 116
measurements, 7
national sample, 9
OECD, 113
participant countries, 4, 5
polemic issue, cognitive sex differences, 115
Raven's Standard Progressive Matrices, 5
region, 9
school activities, 5
school performance, 114
scientific and technological production, 117
SES, 114
sex differences, 115
social indexes, 113
STEM disciplines/jobs, 115
universal concept, 114
World Education Forum in Dakar, 113

T
Threshold Hypothesis (TH), 58
Triarchic Theory of Intelligence, 15
Type of errors
CPM and APM tests, 44
definition, 52
and group of performers, 55
students with cognitive performance, 52
wrong alternative answer, 52
wrong answer alternative, 52

W
Wechsler Adult Intelligence Scales (WAIS), 83
Wechsler scales, 72
World Economic Forum (WEF), 80