Evaluating fluid and crystallized abilities in the performance of an educational process

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Highlights

- Fluid and crystallized abilities were associated with a school learning process;
- Fluid abilities influenced the rate of change in learning;
- Crystallized abilities influenced the final level of learning performance;
- Fluid abilities preceded crystallized abilities when influencing learning;

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Abstract

The fluid and crystallized (*Gf–Gc*) intelligence theory has been used extensively to evaluate the influence of cognitive abilities on educational outcomes within cross-sectional and longitudinal research designs. This study evaluated the contribution of fluid and crystallized abilities in the performance of a one-week instructional process with an old dataset applying a latent curve model (LCM). This allowed for the specification of latent learning growth factors that took into account individual differences in the final level of performance and the rate of learning in the instructional project. Fluid abilities (*Gf*) had a significant impact on the rate of learning, whereas crystallized abilities (*Gc*) had a significant impact on the final learning performance. There was also a significant indirect effect of fluid abilities (*Gf*) onto the final learning performance through crystallized abilities (*Gc*). These findings are in accordance with some of the premises posited by the *Gf*-*Gc* intelligence model.

Keywords: Fluid and crystallized cognitive abilities, learning performance.

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1. Introduction

Apart from representing more or less accurate descriptions of the structure of cognitive abilities, psychometric models of human intelligence serve as conceptual and empirical schemes to predict a number of performance related events, mainly in the educational and occupational domains (McGrew & Wendling, 2010; Schmidt & Hunter, 2004). One of the most studied models concerning educational performance is the Cattell-Horn theory of fluid and crystallized intelligence (*Gf–Gc*), which for the past twenty years has been embodied with the three-stratum theory as an unanimous and acknowledged conceptualization known as the Cattell-Horn-Carroll (CHC) taxonomy of human cognitive abilities (Carroll, 1993; Cattell, 1987; McGrew, 2009). This theory has been suggested as a key basis for intelligence test development (Keith & Reynolds, 2010), but also for interpreting the relationships of cognitive abilities with academic success (McGrew & Wendling, 2010).

This study aims to assess some of the premises of the *Gf–Gc* theory in a particular instructional intervention carried out back in the eighties (Burns, 1980). This goal stems from the need expressed elsewhere concerning the evaluation of old datasets with modern available techniques (McGrew, 2009). As far as it is known, no study has addressed the influence of these broad factors on the performance of brief, but somehow progressive instructional interventions. Therefore, the study evaluates the contribution of fluid and crystallized abilities in the performance of a one-week instructional process by applying a latent curve model (LCM). This methodology allows to model longitudinal individual differences in psychological processes while assessing the influence of potential predictors of change in a variety of fields (Blanch & Aluja, 2010; Garst, Frese, & Molenaar, 2000; Hopwood et al., 2011; Swanson, 2011). An advantage of this technique is that it allows for the specification of two key latent learning factors: final learning performance level and rate or speed of learning. Moreover, the LCM is particularly useful to assess the meaningfulness of between and individual differences in fluid and crystallized cognitive abilities concerning learning achievement (Weinert & Helmke, 1998).

1.1. The CHC taxonomy of cognitive abilities and learning processes

The CHC taxonomy of human cognitive abilities has been widely used when attempting to explain the degree of accomplishment and success in a variety of learning processes (Ackerman, 2000; Cattell, 1963, 1967, 1987; Ferrer & McArdle, 2004; Horn, 1976; Schweizer & Koch, 2002; Skanes, Sullivan, Rowe, & Shannon, 1974). In fact, it has actually been advocated as the framework with the most extensive body of supportive evidence within the educational domain (Newton & McGrew, 2010). For instance, one of the fields in which this theory is presupposed to aid in producing positive changes in education lies in the identification of specific learning disabilities (SLD), particularly when addressing questions about the effectiveness of instructional methods (Flanagan, Fiorello, & Ortiz, 2010).

The probably most comprehensive overview of the relationship of the CHC with academic achievement, however, arises from the analyses of broad and narrow CHC factors with four achievement areas (basic reading skills, reading comprehension, basic math skills, and math reasoning) by three age groups (6-8, 9-13, and 14-19), and including nineteen independent studies (McGrew & Wendling, 2010). This analysis suggested that whereas *Gc* related with the four broad achievement areas, *Gf* was mainly related with basic math skills and math reasoning, even though there were some variations concerning each age group. Interestingly, narrower abilities were suggested as the best choice for the design of instructional interventions in more specific reading or math domains, even though it was also highlighted that most analyzed studies relied in the Woodcock-Johnson Battery, a fact that imposed some limits to any generalization to other available instruments. In sum, the outcomes of this extensive review endorse a CHC based assessment as a functional assistance to undertake the design of educational interventions within SLD as mentioned above.

1.2. Properties of the *Gf–Gc* theory

A fundamental conception of the *Gf–Gc* theory lies in the distinction between the two broad factors labeled as fluid (*Gf*) and crystallized (*Gc*) intelligence, their interrelationships, and their respective influences in academic performance. In general terms, *Gf* represents the basic available cognitive processes that allow for the resolution of abstract and novel problems, whereas *Gc* is conceived as the knowledge acquired through the language, information and concepts that are transferred within the members of a given culture and across cultures (Cattell, 1963, 1987; Horn, 1968). A seminal review of the theory of fluid and crystallized intelligence set forth nine interrelated properties that focused on the conceptualization, interrelationships, and some specific predictions of both broad factors (Cattell, 1963):

(1) Higher loadings of *Gf* and *Gc* on areas demanding problem solving strategies to novel situations, and areas related with earlier learning activities, respectively;

(2) Individual differences in the difference between *Gf* and *Gc* reflect differences in cultural opportunity and interest;

(3) *Gf* attains a maximum at 14-15 years old; *Gc* may increase beyond 28 years old. Besides, *Gf* declines sooner and more sharply than *Gc*;

(4) Schooling and culture relate with higher levels of variability in *Gc* than in *Gf*;

(5) *Gf* is biologically driven, whereas *Gc* depends on cultural influences;

(6) Short-term fluctuations in *Gf* are physiologically driven, while *Gc* fluctuations are caused by practice and motivational factors;

(7) *Gf* is more sensitive to brain-damage, even though *Gc* can also be affected by changes in particular and localized abilities (i.e., verbal);

(8) *Gf* and *Gc* levels at a given moment are a growth function of past *Gf* levels, thus, both factors are expected to be correlated;

(9) The effect of *Gf* will be higher than the effect of *Gc* in the rate of learning in new areas, but lower than the effect of *Gc* in already studied areas;

1.3. Structural, kinematic and dynamical predictions

When attempting to assess the properties summarized above, the *Gf–Gc* theory has been addressed from structural, kinematic, and dynamic predictions (Cattell, 1963, 1987; McArdle, Hamagami, Meredith, & Bradway, 2000). Structural predictions suggest the inadequacy of a general intelligence factor (*g*) alone to represent observed variations in cognitive abilities, with two distinguishable broad factors being instead necessary to account for a given set of abilities interrelations (properties 1, 4, 5). Studies from the structural approach have addressed the associations of *Gf* and *Gc* with prominent psychometric general intelligence models, indicating supportive evidence for the *Gf–Gc* theory (Johnson & Bouchard, 2005; Kan, Kievit, Dolan, & van der Maas, 2011; Kvist & Gustafsson, 2008).

Kinematic predictions attempt to explain the mechanisms and mutually influencing variations in *Gf* and *Gc* from early developmental stages. Apparently, there should be additional gains of *Gc*, although with a degradation in *Gf* when initiating adulthood and through the life span (properties 2, 3, 6 and 7). The development of *Gf* and *Gc* has also been generally supported by some empirical studies as suggested by *Gf–Gc* theory (Ackerman, 1996; McArdle et al., 2000; Schaie, 1994).

Dynamic predictions propose that the investment of *Gf* influences the course of *Gc* and educational outcomes during the schooling period in combination with third factors such as interests or memory (Ackerman, 1996; Ackerman & Heggestad, 1997). Besides, this approach examines how *Gf* and *Gc* connect with a number of learning related issues (properties 8 and 9). This course of action, however, has probably shown the most contentious and inconclusive outcomes (Ferrer & McArdle, 2004; Gustafsson & Undheim, 1992; Schmidt & Crano, 1974; Schweizer & Koch, 2002). For instance, the cross-lagged causal relationship from *Gf* towards the development of *Gc* suggested to be supported only for a middle-socioeconomic-status group of elementary schoolchildren, but not supported for low-socioeconomic-status elementary schoolchildren (Schmidt & Crano, 1974). Moreover, the notion of a cross-lagged *Gf–Gc* relationship has been challenged by non-supportive outcomes (Gustafsson & Undheim, 1992), plausible *Gf* → learning → *Gc* mediation mechanisms for younger rather than for older participants (Schweizer & Koch, 2002), and by the notion that the influence of *Gf* onto *Gc* might well be happening before schooling (Ferrer & McArdle, 2004).

1.4. The present study

The dynamic standpoint that considers the influence of the *Gf–Gc* complex in educational performance has been mostly focused on the development of intellectual ability in the long-term. This has involved empirical and theoretical analyses involving periods of time of a year or more in the schooling stage (Gustafsson & Undheim, 1992; Swanson, 2011), in the course of adult years (Ackerman, 1996; Schaie, 1994), or even across the whole life-span (Ferrer & McArdle, 2004; Horn, 1968; McArdle et al., 2000). Moreover, it has been argued that the influence of *Gf* on *Gc*, and their associations with learning outcomes could also be noticed within narrower periods of time, advocating for cross-sectional designs to ascertain the *Gf–Gc* interrelationship with learning experiences (Schweizer & Koch, 2002). Nevertheless, the outcomes derived from the dynamic approach also suggest that the *Gf–Gc* uneven link might comply with more intricate arrangements than cross-lagged relationships, particularly when influencing learning performance (Hunt, 2000; McArdle et al., 2000; Schweizer & Koch, 2002). For instance, it has been suggested that the *Gf–Gc* investment hypothesis could be accounted for by the specific premises of the mutualism model, a reciprocal causation framework suitable to delineate and clarify a number of outcomes in research about intelligence (van der Maas et al., 2006).

Within *Gf–Gc* theory, there are three different predictions advanced to assess the investment hypothesis. First, a *Gf* influence on *Gc*, but no influence of *Gc* on *Gf*. Second, a dependent process (*Gc*) would start to grow only beyond a certain point in the basic process (*Gf*). Third, a higher speed of growth for processes related with *Gf* than with processes related with *Gc*. Therefore, another possibility to assess dynamic predictions derived from the *Gf–Gc* theory could be to consider educational experiences carried out within shorter although somehow progressive and more gradual learning periods with a regular performance assessment. As far as it is known, the associations of cognitive abilities with the accomplishment in such sort of brief systematically designed learning experiences have been rather unexplored.

This study aimed to evaluate the interrelationships embedded within the *Gf–Gc* theory and their contribution to the performance in a brief instructional process intended to teach novel concepts and procedures. There were two main research questions. First of all, it was examined whether the ninth property set out by Cattell was partially met or not (Cattell, 1963). Thus, a stronger effect of *Gf* than of *Gc* on the rate of learning dimension should be observed. Moreover, *Gf* should exert a stronger influence on the rate of learning than on the final learning performance dimension in accordance with the third prediction derived from the mutualism model when addressing the investment hypothesis. The second research question lies in Cattell's (8) property and the first prediction from the mutualism model. If there exists a causal precedence of *Gf* over *Gc* then there should be an indirect effect of *Gf* through *Gc* and onto the learning performance dimensions (*Gf* → *Gc* → Learning), whereas there should not be indirect effects from *Gc* through *Gf* and onto academic performance (*Gc* → *Gf* → Learning).

2. Method

2.1. Data set

There were two requisites to address the goals in the present study. In accounting for individual differences in cognitive abilities, past research about the *Gf*–*Gc* model has stressed the convenience of homogeneous samples to control for cultural and educational factors (Kan et al., 2011; Kvist & Gustafsson, 2008). Besides, the data should contain systematic and periodical information about the performance in some sort of instructional process in a new area. A data set from the Human Cognitive Abilities (HCA) project meeting these two requirements is the BURN11 database, available at the Woodcock-Muñoz Foundation (WMF, http://www.iqscorner.com/2008/05/wmf-human-cognitive-abilities-archive_07.html) Human Cognitive Abilities Archive Project (Burns, 1980; McGrew, 2009).

2.2. Participants and general procedure

These data correspond to 101 students in a California high school (51 males and 50 females). Students enrolled in 10^{th} to 12^{th} grades went through an instructional project composed of four hierarchical learning units during seven consecutive schooling days, from Thursday to Friday. Students fulfilled cognitive abilities measures in the first three days. The instructional project and achievement testing were performed in the next four days.

2.3. Instructional intervention

The instructional intervention comprised a two-phase description of an imaginary science designated as *Xenograde Systems*: a lecture/discussion phase, and an individual working phase. The curricular materials encompassed the four learning units and were delivered in instructional booklets of between four and five pages, with written prose, diagrams, graphs, and tables. Unit 1 defined basic terms and operations. Unit 2 showed rules and procedures for reading graphs. Unit 3 introduced new facts and concepts that increased the system complexity. Unit 4 presented the fully operating system bringing together the concepts from the previous units. An in-depth description of the project can be seen in the original study (Burns, 1980). The outcomes of that intervention suggested differential aptitude-learning relations somehow matching the current research questions: *Gc* was related with learning throughout the instructional intervention, whereas *Gf* was related with learning depending on the point in time that it was measured (Burns, 1980; Burns & Gallini, 1983).

2.4. Measures

The BURN11 database consists in a correlation matrix of 19 cognitive abilities and 4 achievement measures, even though only 11 of these abilities were used in the current study. Table 1 shows an overview of these measures, their corresponding broad / narrow factor, their means and standard deviations, and their reliabilities as reported in the original study (Burns, 1980).

In addition, there was one achievement measure per learning unit. These four measures assessed the performance on the instructional project at three levels of learning: knowledge, comprehension, and application. The four tests were on the same scale and consisted in four-distractor multiple-choice achievement tests developed by the experimenter. Each of the four achievement measures had 18, 14, 16 and 16 items, whereas Cronbach's reliabilities were .83, .76, .80, and .76, respectively. Figure 1 shows the means and variances, indicating that the achievement growth process fluctuated across the four observation points as a sinusoid-like pattern, with a rather flat growth in the first three achievement measures, and with a pronounced drop in the last achievement measure. This marked decrease in the last measure, was likely due to the increasing difficulty in the learning unit 4, where the full *Xenograde System* was presented and became highly complex. Unfortunately, individual growth curves could not be modelled because raw data were not available within the BURN11 dataset.

2.5. Data analyses

The data were analyzed in two stages. First, a confirmatory factor analysis (CFA) assessed the dimensionality of the *Gf–Gc* model. The CFA specification took into account the highest loadings (above .50) in the principal components analysis results derived from the original study, and the theoretical basis concerning the loadings of cognitive tests on the *Gf–Gc* representation (Burns, 1980). The measures defined as loading in *Gf* were Series, Matrices, Card Rotations, and Map Planning. The measures loading on *Gc* were the five comprehensive tests of basic skills (CTBS), Vocabulary II and Division.

Second, a LGC model based in four time points was specified with the four consecutive achievement measures as observed indicators, and an intercept (π_0) and slope (π_1) latent growth factors characterizing the status or baseline at a given point in time and the growth rate in achievement, respectively (Curran & Hussong, 2002; Muthén & Curran, 1997; Willet & Sayer, 1994). There were two kinds of models:

(1) The unconditional model represented the change that each person underwent in time, indicating individual differences in the intercept and slope growth factors.

This model provided an indication of the global performance in the instructional intervention;

(2) The conditional model with predictors of change represented the influence of the *Gf* and *Gc* factors on the individual growth factors. This model furnished an estimation of the magnitude and direction of the effects of *Gf* and *Gc* on both, intercept and slope;

For each of the four achievement measures, the corresponding intercept's four parameters were fixed to unity, and the slope's four parameters were fixed to –3, –2, –1, and 0. The origin of time equalling zero at the last achievement measure intended to evaluate the hypothesized relationships at the end of the instructional process (Biesanz, Deeb-Sossa, Papadakis, Bollen, & Curran, 2004; Mehta & West, 2000; Stoel & van den Wittenboer, 2003). The error term in the fourth achievement measure was correlated with the three error terms of the three previous achievement measures because the fourth learning unit comprised concepts addressed in the previous three learning units. The first research question was evaluated with three competing models. The second research question was evaluated by comparing the two causal directions between *Gf* and *Gc* ($Gf \rightarrow Gf$ and $Gc \rightarrow Gf$) and determining whether there were any indirect effects onto the learning dimensions of intercept and slope.

3. Results

Figure 2 shows the *Gf*–*Gc* model CFA. This resulted in an acceptable fit to the observed data ($\chi^2[39] = 55.54$ ($p < .05$), TLI = .96, CFI = .97, RMSEA = .06, SRMR = .05, AIC = 109.54), with significant estimates for all observed measures ($p < .001$), and a significant .33 ($p < .01$) correlation between the *Gf* and *Gc* factors. These outcomes indicated a fair representation of the observed cognitive measures, and that the latent factors could be subsequently used in the prediction of achievement in the assessed instructional program.

The initial linear LGC model did not fit the data well, with a significant χ^2 value for 2 degrees of freedom (95.69, $p < .001$), inappropriate fit indices (TLI = .64, CFI = .93, RMSEA = .68, SRMR = .09. AIC = 119.69), and abnormal estimates such as negative intercept and slope variances (see Table 2). There was a better fit with a non-linear model (Figure 3), with freed parameters in the second and third slope loadings. Besides, there were equal achievement error variances for the third and fourth learning units which also had the same number of items, and the error variance set to zero for the second learning unit because of its lowest value in the initial model ($\chi^2[2] = 2.25$, TLI = .99, CFI = 1.00, RMSEA = .03, SRMR = .02. AIC = 26.25).

This model represented fairly well the between-individual variability of performance in the instructional process under study (see Table 2). Mean intercept and slope estimates were significant ($\mu_{\pi 0} = 9.46$, $\mu_{\pi 1} = -1.31$; $p < .001$), indicating that there were significant individual differences in mean final achievement at the end of the project, with a significant mean decrease in the overall performance of –1.31 for a unit change in the time score. There were also significant estimates for the intercept and slope variances ($\sigma^2_{\pi 0} = 7.01$, $\sigma^2_{\pi 1} = .82$; $p < .01$) suggesting individual differences in the final levels and in the decreasing rate of achievement. The positive correlation between the intercept and slope factors was also significant ($\sigma_{\pi 0 \pi 1} = .55$; $p < .05$), suggesting that individuals with higher final levels of achievement had lower achievement decrements, whereas students with lower final achievement scores experienced the higher achievement decrements over the instructional program.

The conditional model allowed testing whether there were significant relationships between the *Gf–Gc* factors with the intercept and slope growth factors

(Figure 4). Models A to C assessed the links of *Gf* and *Gc* with the intercept and slope growth factors. Models A and B show the hypothesized relationship concerning the first research question. Both models characterized the simultaneous effects of *Gf* and *Gc* on the growth factors. Model A showed a significant negative effect of *Gf* on the slope factor (–.23) and a null effect on the intercept factor (.07), whereas *Gc* had a positive significant effect on the intercept factor (.49) although a null effect on the slope factor (–.06). Model B assumed a zero effect of *Gf* and *Gc* on the intercept and slope factors, respectively. There were no significant chi-square differences between models A and B ($\Delta\chi^2[2] = 0.64$), with a fair model fit indicating an acceptable representation of the observed relationships. Model C in turn assumed an asymmetrical relationship to that hypothesized, *Gf* related with the intercept and not with the slope, and *Gc* related with the slope and not with the intercept. This model showed, however, a significant deterioration in model fit in respect to either of the previous A and B models, with a significant chi-square difference with model A ($\Delta\chi^2[2] = 25.42$, $p< .001$). The significant effects of *Gf* and *Gc* onto each growth factor observed in models A or B, suggested that higher *Gf* scorers had lower decrements in achievement, whereas higher *Gc* scorers had higher final achievement levels. This was in line with the expectations of the first research question addressing the effects of *Gf* and *Gc* on the rate of change and final learning levels in the instructional intervention.

Models D and E evaluated the causal precedence of *Gf* – *Gc*. In model D, there was a significant indirect effect of *Gc* through *Gf* on the intercept (.11, $p < .05$; 95%CI = [.01, 1.12]) but not on the slope factor (–.09; 95%CI = [–.18, .01]). In model E, there was a significant indirect effect of *Gf* through *Gc* on the intercept (.18, $p < .01$; 95%CI = [.14, .87]), but not on the slope factor (–.04; 95%CI = [–.11, .02]). However, model fit was better for model E than for model D, particularly in terms of its chi-square and AIC values. These outcomes were coherent with the second research question, lending support to the causal precedence of *Gf* over *Gc* and onto learning performance.

4. Discussion

The present study extended some of the dynamical premises stated by the *Gf–Gc* model to the learning performance in a short instructional experience. A latent curve model (LCM) represented two main learning dimensions: rate of learning and final learning performance level. The research questions addressed the variation in *Gf* and *Gc* cognitive abilities when influencing these two meaningful learning dimensions. First, stronger effects of *Gf* than *Gc* were expected in the rate of learning, and stronger effects of *Gf* on the rate of learning than on the final learning level. Second, a significant indirect effect was expected from *Gf* through *Gc* and to the learning dimensions, whereas a non-significant indirect effect was expected from *Gc* through *Gf* and to the learning dimensions.

The findings rendered support to the first research question, concerning the interrelationship of *Gf* and *Gc* and their associations with learning performance. When considering the effects of the two broad factors and as suggested by the 9th property established by the *Gf-Gc* theory (Cattell, 1963), *Gf* had a higher influence in the rate of learning than *Gc*. Similarly, and in connection with the third prediction embedded within the mutualism model (van der Maas et al., 2006), *Gf* had a stronger effect on the rate of learning than on the final performance level of the instructional process. The outcomes also supported the second research question concerning the causal precedence of *Gf* over *Gc*. The "$Gf \rightarrow Gc \rightarrow$ Learning" model yielded a significant indirect effect from *Gf* through *Gc* and in the final learning performance level, whereas there was not a significant indirect effect in the rate of learning dimension. Thus, despite the robust direct effect of *Gc* on final performance, this learning dimension was also indirectly influenced by *Gf* through *Gc*. It should be remarked that the assessment of indirect effects had the aim of evaluating the likelihood of the causal precedence of *Gf* over *Gc*, rather than building a full explanatory model of the observed relationships. While there were indirect effects in both models (D and E, Figure 4) the "*Gf* → *Gc* → Learning" model yielded a better fit than its counterpart ("*Gc* → *Gf* → Learning). Taken together, these findings suggest in fact that the interplay of both broad *Gf* and *Gc* factors contributed significantly to learning performance in the instructional intervention. Their interrelationship was therefore more important for learning, than the unique contribution of a single set of these broad cognitive abilities.

4.1. Fluid and crystallized abilities in learning performance

The key finding in the present research is probably the markedly uneven and significant impact of *Gf* and *Gc* over two conceptually differentiated learning growth factors, rate of learning and final performance, respectively. This indicates that these broad intertwined and representative factors of cognitive abilities influenced the performance in the instructional experience through the different hypothesized pathways. *Gf* was in fact more predictive of the speed at which learning took place than of the final performance in that instructional project, whereas *Gc* was in turn the stronger determinant in the final performance learning dimension.

This asymmetry in the *Gf*-*Gc* set of cognitive abilities when related to each learning factor substantiates the outcomes reported in past research. For instance, the findings reported in the original study with the same data suggested *Gf* instability and *Gc* stability (Burns, 1980; Burns & Gallini, 1983). In the current study, the *Gf* instability was reflected by its relationship with the dynamic growth factor of rate of learning, whereas the *Gc* stability in turn was mirrored by its stronger association with the compact and static growth factor of final level of performance. Moreover, *Gf* and *Gc* were suggested as being respectively connected with the content and method of instruction (Burns, 1980). It has been suggested that exposure to learning situations dealing with original contents could be cognitively burdensome and that *Gf* would be more predictive of the performance in such type of learning activities (Snow & Lohman, 1984). In contrast, there is evidence indicating a stronger effect of *Gc* than of *Gf* on current events knowledge, a preceding networked informational structure where new inputs of knowledge are attached by means of associative strategies (Hambrick, Pink, Meinz, Pettibone, & Oswald, 2008). Because the contents delivered in the instructional project were new, an imaginary science system labeled as *Xenograde Systems*, it follows that *Gf* should have shown a stronger effect on learning as a whole than *Gc*. However, the influence of *Gf* on learning as conceptualized in the present study followed two clear distinctive pathways, a direct effect on the speed of learning, and an indirect effect of *Gf* through *Gc* on the final level of performance in the learning process.

While this outcome may be connotative of the importance of *Gf* in instructional processes, it should be noticed that the strongest path linking the cognitive abilities and the learning factors was that between *Gc* and final learning performance level. This can be supportive of the notion of some sort of interchange (i.e., investment) between both sets of cognitive abilities. Obviously, and from a purely statistical point of view, there could be no indirect effect at all of *Gf* on the final performance with a lower effect of *Gc*. From a conceptual point of view and as already suggested (Burns, 1980), *Gc* might have a more robust link with the method than with the content of instruction, perhaps as some sort of methodological device useful to determine a procedure to provide a solution to a given problem (Hunt, 2000). Thus, the present outcomes may be viewed as if *Gf* and *Gc* operated interdependently through both elements of the instructional application to produce the observed set of relationships.

4.2. Implications for the design of instructional interventions

The *Gf* – *Gc* theory may be of practical utility to predict educational performance outcomes during the implementation of instructional interventions. The evaluation of these broad intelligence factors prior to any specific intervention may allow education planners to make more informed decisions (McGrew & Wendling, 2010). This is in line with optional instructional treatments to match individual differences in *Gf* or *Gc*, an interaction that is further influenced by task and/or situational variables as suggested by aptitude-treatment interaction (ATI) theory (Snow & Lohman, 1984). One of the key principles of ATI lies in that higher structured instruction is more beneficial for students with lower ability, while low structured instruction is more beneficial for students with higher ability. Furthermore, individuals that are more anxious might attain an optimum level of learning in highly structured instructional interventions, with non-anxious individuals being fonder of low structured learning environments. For instance, learning goals that are novel or complex, or instruction with a more inductive or unstructured organization may impose higher requirements on *Gf*. On the other hand, learning goals that require the recovering and modification of already known schemes and models to more familiar tasks, particularly within the language domain, may impose higher requirements on *Gc* (Ackerman & Beier, 2006; Hunt, 2000; Snow & Swanson, 1992).

The approach that guided the present research was the conceptualization of learning in terms of two latent factors, speed or learning rate and final learning achievement level. Both, *Gf* and *Gc* cognitive abilities influenced learning even though through different but meaningful pathways. Educators and curriculum designers might bear in mind the evaluation of these two important broad cognitive abilities when conceiving the design of comprehensive instructional interventions and curricular materials addressed to individuals with specific learning disabilities (SDL).

Nevertheless, the intervention within more focused and limited areas, should probably rely in the evaluation of consequently narrower abilities within the CHC taxonomy (McGrew & Wendling, 2010). The outcomes in this research suggest that individuals with different aptitudes learn differently, and that instructional design should tailor these individual differences apart from other considerations concerning situational or circumstantial requirements.

4.3. Limitations and future research

A limitation in the present study is the lower number of tests used to conceptualize the *Gf–Gc* model. The available data in which this study is based precluded the possibility to include a higher number of tests batteries than that reported elsewhere (Burns, 1980; Johnson & Bouchard, 2005). Nonetheless, the confirmatory factor analyses of this model suggested that this conceptualization represented the observed data fairly well.

Furthermore, the Cattell's ninth property evaluated here could only be partially assessed with the present data. There was no information in this data set concerning educational performance in already studied areas, which could have provided a more complete evaluation of this property. In addition, there were no data about motivation, interests, personality, or situational factors such as parental involvement. These have been considered as important elements for the evaluation of performance in educational process because of its close relationship with achievement in school or occupational domains (Ackerman, Chamorro-Premuzic, & Furnham, 2011; Ackerman & Heggestad, 1997; Blanch & Aluja, 2013; Furnham, Monsen, & Ahmetoglu, 2009).

Moreover, it should be taken into account that the number of participants was rather low in this dataset. With a large number of variables and within the LCM approach, a higher number of participants would have been highly desirable. Sample size is related with statistical power, with the number of available time points per individual, and with the number of parameters to be estimated from a given model (Muthén & Curran, 1997). Thus, lower sample sizes tend to relate with lower statistical power. The reduced number of participants is also a hindrance when attempting to generalize the present findings beyond these data. The low number of participants could also have influenced in the non-linear, and consequently, more complex trajectory observed in the global achievement of the instructional intervention. However, the observed non-linear trend could also be due to the very limited time span considered of only four days. Non-linear trends appear to be common in developmental and educational research assessing change processes, thus, using an adequate number of measurement occasions and selection of commensurate samples are important concerns to be addressed in future studies within this field (Grimm, Ram, & Hamagami, 2011).

The present study analyzed data from past research about an instructional intervention bound to a limited number of available measures on cognitive abilities (Burns, 1980; Burns & Gallini, 1983), which was modeled in accordance with some of the premises advanced by the *Gf–Gc* Cattell-Horn theory. However, this model has been integrated with the three-stratum intelligence model originating a comprehensive detailed taxonomy of human cognitive abilities, the Cattell-Horn-Carroll model (CHC), (Carroll, 1993; Cattell, 1987; McGrew, 2009; Newton & McGrew, 2010). This model is particularly useful in future research addressed to unify the terminology and classification of narrower abilities measured by a number of intelligence tests. Moreover, and from a more pragmatic approach, the CHC has been considered as a suitable framework to evaluate and understand the association of cognitive abilities with academic achievement in the identification of specific learning disabilities (SLD) and evaluation of the effectiveness of instructional methods (Flanagan et al., 2010; McGrew & Wendling, 2010).

4.4. Conclusion

The dynamical approach of the *Gf–Gc* intelligence theory has been used extensively to predict educational outcomes, although most of the studies to date have been centered on long-term developmental associations or cross-sectional studies. Past research has shown support for the investment hypothesis and the *Gf – Gc* theory when assessing long term educational processes (Ackerman, 1996; Ferrer & McArdle, 2004; Gustafsson & Undheim, 1992; Horn, 1968; McArdle et al., 2000; Swanson, 2011). This study assessed some of the *Gf–Gc* premises when related with a final attained level and a rate of learning growth factors in a shorter one-week instructional process. The *Gf* dimension had a significant direct influence in the rate of learning, although it was also an indirect meaningful predictor of final learning performance when acting through the *Gc* dimension. Thus, cognitive abilities encapsulated within the *Gf–Gc* theory operated in a proportionate combination to impact learning as suggested in past empirical research works (Ferrer & McArdle, 2004; Schweizer & Koch, 2002; Vock, Preckel, & Holling, 2011). The outcomes in the present research fit reasonably with some predictions concerning the *Gf–Gc* theory and suggest that some of the premises derived from the investment hypothesis could also hold concerning short-term educational activities of the kind evaluated here. The findings may bear some useful implications for the evaluation of instructional design, particularly concerning previous task experience and instructional task configuration (Ackerman & Beier, 2006; Snow & Swanson, 1992), or in interventions specifically undertaken by individuals with specific learning disabilities (Flanagan et al., 2010; McGrew & Wendling, 2010).

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Tables and Figures

Table 1

Cognitive abilities measures from Burns (1980) used in the present study

Measure	Description	Broad / Narrow Factors*	Mean (SD)	Reliability
Vocabulary II	Five-choice synonym test	Verbal comprehension (V)	12.53 (4.60)	.75
Division	Divide two and three digit numbers by single-digit numbers	Number Facility (N)	18.79 (10.77)	.92
CTBS Vocabulary	Four choice synonym test	Crystallized intelligence (Gc)	22.21 (7.13)	.90
CTBS Comprehension	Answer questions about stories, poems and letters just read	Crystallized intelligence (Gc)	24.89 (7.77)	.90
CTBS Computation	Arithmetic: addition, subtraction, multiplication and division	Crystallized intelligence (Gc)	27.69 (9.53)	.93
CTBS Concepts	Recognize the appropriate numerical operation or concept	Crystallized intelligence (Gc)	16.49 (5.32)	.84
CTBS Applications	Comprehend a problem and perform numerical operations	Crystallized intelligence (Gc)	10.11 (4.23)	.84
Card Rotations	Decide if irregular shapes are rotations or side-flipped of original shape	Spatial Relations (SR)	87.64 (33.25)	.90
Map Planning	Determine the shortest route between two points	Spatial Scanning (SS)	17.85 (4.74)	.71
Series	Complete a progressive series of figures	Fluid intelligence (Gf)	8.08 (1.67)	.49
Matrices	Complete a design or matrix of figures that is incompletely shown	Fluid intelligence (Gf)	9.07 (2.20)	.67

*In accordance with the Human Cognitive Abilities (HCA) project definitions;
CTBS: Comprehensive Tests of Basic Skills, (CTB/McGraw-Hill, 1973);

Table 2
Between-individual differences in change in achievement measurements

Parameters and fit indices	Linear	Non linear
Intercept mean ($\mu_{\pi 0}$)	8.98***	9.46***
Slope mean ($\mu_{\pi 1}$)	–1.26***	–1.31***
Intercept variance ($\sigma^2_{\pi 0}$)	–12.65**	7.01***
Slope variance ($\sigma^2_{\pi 1}$)	–3.40**	.82*
Intercept-slope correlation ($\sigma_{\pi 0 \pi 1}$)	---	.55*
Error variance ($\sigma^2_{\varepsilon 1}$)	10.56***	4.72**
Error variance ($\sigma^2_{\varepsilon 2}$)	1.22	0^f
Error variance ($\sigma^2_{\varepsilon 3}$)	15.35***	4.74***
Error variance ($\sigma^2_{\varepsilon 4}$)	24.63***	4.74***
χ^2	95.69***	2.25
Df	2	2
TLI	.64	.99
CFI	.93	1.00
RMSEA	.68	.03
SRMR	.09	.02
AIC	119.69	26.25

Note.
**p*< 0.05; ***p*< 0.01; ****p*< 0.001; ^{f} Fixed parameter;

Figure 1. Mean and variance vectors in the four achievement measures

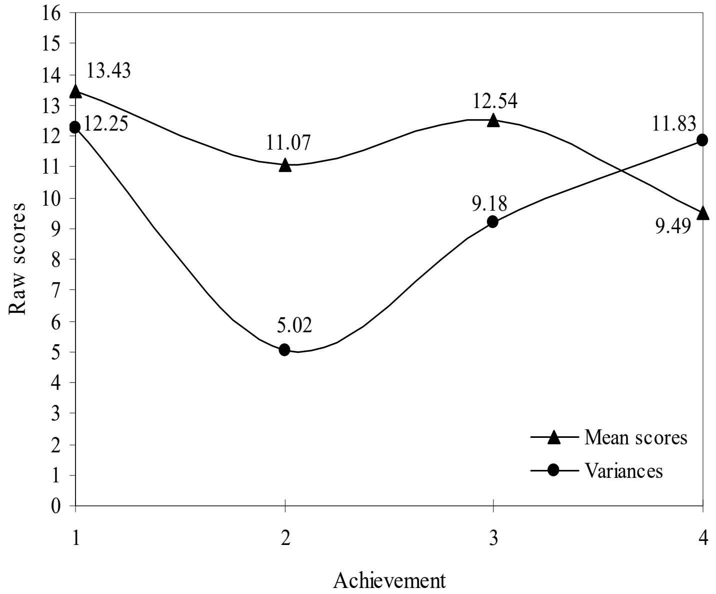


Figure 2. Confirmatory factor analyses of fluid (*Gf*) and crystallized (*Gc*) intelligence measures.

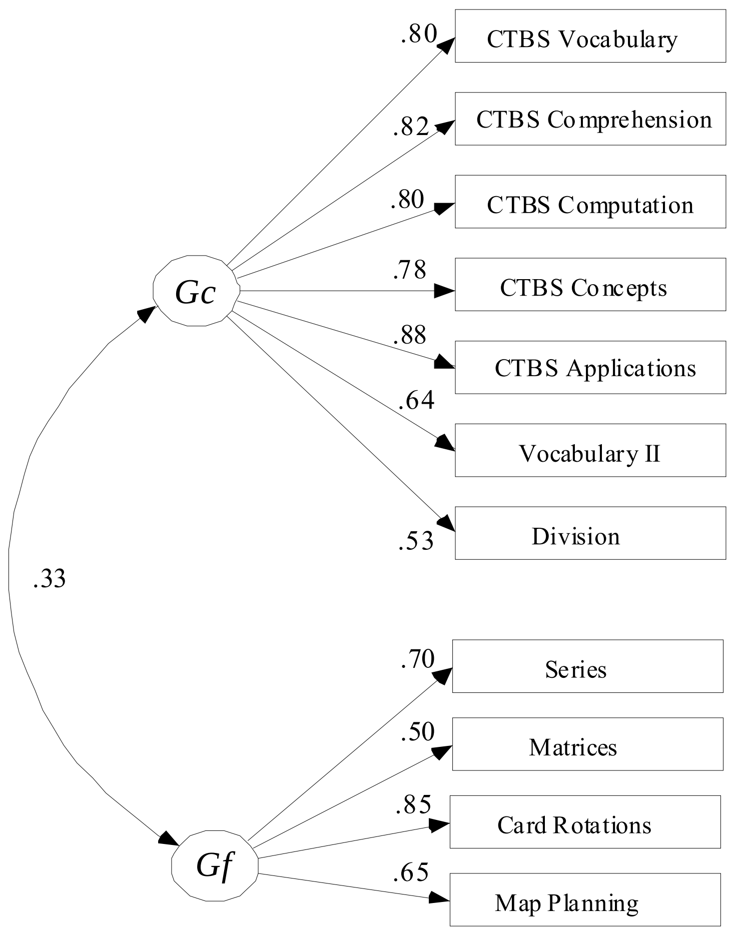
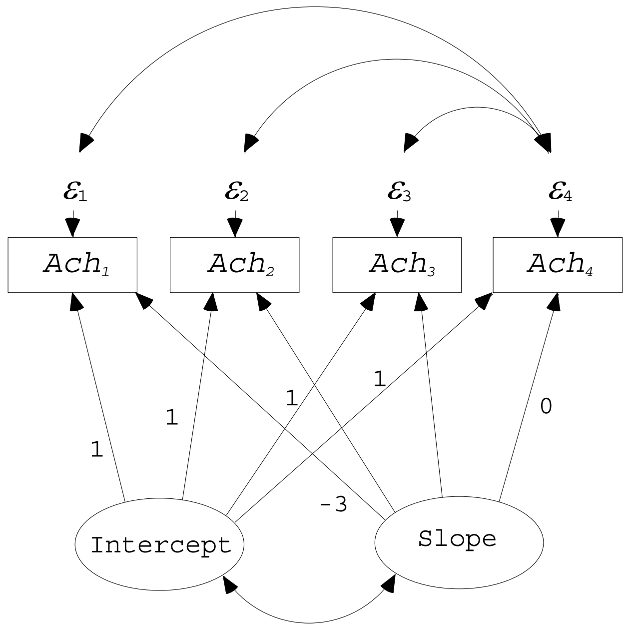


Figure 3. Non-linear growth model in achievement (*Ach*$_n$).



SLOPE

Figure 4. Between-individual differences explanatory models for growth in achievement with *Gf* and *Gc* as predictors of change; *Int*: Intercept; *Slo*: Slope; Intercept and slope error terms were correlated in all models (**p*< 0.05; ***p*< 0.01; ****p*< 0.001).