BRIEF RESEARCH PAPER

Intelligence subcomponents and their relationship to general knowledge

Francisco Buades-Sitjar [iD] · Jon Andoni Duñabeitia [iD]

Abstract Research on the different components of fluid intelligence and how they relate to each other is quite extensive. Meanwhile, when it comes to crystallized intelligence, only vocabulary size has been somewhat thoroughly studied, while other key components, such as general knowledge, remain largely unexplored. This study aims to further our understanding of general knowledge as a key component of crystallized intelligence, and of general intelligence as a whole, by exploring how it is influenced by other components of intelligence. To that end, we had 90 participants complete an extensive general knowledge questionnaire, as well as several tests aimed at measuring various components of intelligence, and computed linear regressions to examine how these various components influence general knowledge scores. Our results reveal that, even though general intelligence is able to predict general knowledge scores, only some specific components of intelligence have a direct positive impact on general knowledge. These findings are discussed in regard to intellectual investment theories on the relationship between fluid and crystallized intelligence.

F. Buades-Sitjar · J. A. Duñabeitia (✉)
Centro de Investigación Nebrija en Cognición,
Universidad Nebrija, Madrid, Spain
e-mail: jdunabeitia@nebrija.es

J. A. Duñabeitia
Department of Languages and Culture, The Arctic
University of Norway, Tromsø, Norway

Introduction

It has been well over a century since Spearman published his works on what is reputed to be the foundation of most subsequent views on intelligence: the finding of a general factor, g, that explained a significant variance of all intelligence measures (Spearman 1904). Yet, even after all this time, new theories, definitions and taxonomies of intelligence keep being formulated —see (Kaufman et al. 2013) for a review on the most recent ones—, which highlights how little consensus has been achieved when it comes to creating a comprehensive definition and taxonomy, and belies how much is yet to be discovered about the construct.

There is, however, one view of intelligence that stands out as being generally accepted by the scientific community: Cattell's division of intelligence into a fluid and a crystallized component (Cattell 1943). Through this lens, the fluid component of intelligence would comprise cognitive abilities that are not based on previously acquired knowledge, such as logical reasoning or spatial skills. Meanwhile, the crystallized component comprises all the knowledge that a person

has acquired throughout their lifespan, both declarative —vocabulary, academic knowledge…— and procedural —how to use certain software, how to play an instrument…—. This is a simple yet powerful division, as it allows us to draw a distinction between intelligence as the processing and manipulation of new information, and intelligence as the storing and retrieval of old information. It has also served as the backbone of new, more elaborate taxonomies of intelligence, such as the Cattell-Horn-Carroll theory of cognitive abilities (Carroll 1993), which divides intelligence into a first stratum containing over 70 specific cognitive abilities, a second stratum containing eight more general abilities —including fluid and crystallized intelligence—, and a third stratum representing the general factor g.

On an empirical level, several pieces of research support this division. For instance, studies have found that each type of intelligence is affected differently by age: while fluid intelligence tends to peak at around one's mid-to-late twenties (Furnham & Moutafi 2012; Kievit et al. 2014), certain aspects of crystallized intelligence peak well into middle age or later (Aguasvivas et al. 2020; Brysbaert et al. 2016; Buades-Sitjar et al. 2021b). Other studies have found that fluid and crystallized intelligence each provide unique benefits in decision-making tasks (Bruine de Bruin et al. 2012), and that they have a different impact on academic achievement depending on age (Ackerman 1996). Furthermore, recent genetic and neuroimaging studies have found that certain neural structures and processes differentially influence and facilitate fluid and crystallized intelligence (Christoforou et al. 2014; Tadayon et al. 2020).

One crucial caveat to keep in mind, however, is that Cattell's division does not imply that fluid and crystallized intelligence are completely independent from one another. In fact, Cattell himself suggested a theory of "intellectual investment" to explain how these two constructs interact (Cattell 1963, 1967), posing that fluid intelligence acts as a sort of "capital" that people can invest in the process of learning and acquiring knowledge. Hence, a high level of fluid intelligence would facilitate the attainment of new knowledge, resulting in a higher level of crystallized intelligence, but only if an active effort has been put into cultivating said knowledge. Various pieces of research support this kind of interaction, finding that both fluid and crystallized intelligence are correlated,

and that fluid intelligence can, to some extent, be used to predict crystallized intelligence (Ackerman 1996; Ackerman et al. 2001; Furnham and Chamorro-Premuzic 2006; Thorsen et al. 2014). Of particular importance are the studies by Ackerman (Ackerman 1996), who expands on this theory by highlighting the importance of personality and interests as the non-ability factors that determine the time and effort that a person puts into the process of learning. In a similar fashion, previously acquired knowledge such as the languages we speak (Grundy, 2020; Winskel and Perea 2021), our interiorized cultural norms (Freire & Pammer 2020), or even specific skills (Kolinsky & Verhaeghe 2017) has been shown to shape the way we tackle and solve certain fluid problems. Finally, Valentin Kvist and Gustafsson (2008) provide further insight into this relationship by examining how crystalized intelligence moderates the relationship between fluid intelligence and Spearman's g factor. Their study showed that the correlation between fluid intelligence and g was almost perfect when all individuals in a sample had had the same learning opportunities and experiences. However, when this was not case, the correlation index dropped down to 0.83 which, still being considerably high, showed that individuals who had acquired knowledge that was better suited to the tests at hand could overcome differences in fluid intelligence.

For all its advantages, Cattell's division is not without its flaws, though. While its general and simplistic nature is a solid first step toward stablishing a taxonomy of intelligence, it also makes it insufficiently specific, and further subdivisions of both fluid and crystallized intelligence are still required. For instance, when it comes to fluid intelligence, drawing conclusions from a series of premises —i.e., reasoning— and the ability to mentally manipulate visual information are clearly separate cognitive skills that must be individually evaluated (Bart et al. 1980; Langdon & Warrington 2000; Liang et al. 2020). This issue becomes even more egregious when it comes to crystallized intelligence. First, there are endless types and areas of knowledge, making it virtually impossible to create a comprehensive and concise taxonomy. Second, and most importantly, measuring a person's knowledge, even in one specific area, is infinitely more time and resource-consuming than measuring a person's reasoning or spatial ability. For example, in a classical fluid reasoning task, a participant is shown a

series of symbols that follow a logical pattern, and the participant must discover said pattern and choose the symbol that will continue the series. In this task, the same cognitive skill is applied to each item, and we can create progressively more difficult items by increasing the complexity of the pattern. However, when measuring acquired knowledge —especially declarative knowledge— each item represents a unique piece of knowledge that a person may or may not have acquired. Therefore, an almost infinite number of items would be required to measure even just one specific aspect of a person's knowledge, let alone its entirety. Hence, when picking an aspect of crystallized intelligence to study, it is crucial that (A) it be culturally relevant, so as to maximize the benefits of the invested resources, and (B) that each piece of knowledge —i.e., each item— can be measured quickly and easily, to be able to cover as much of that area of knowledge as possible.

Along these lines, vocabulary size has been a widely favored topic within research on crystallized intelligence, and for good reason. First, its cultural relevance is undisputed, as language, and hence vocabulary, is common to all human beings. Second, it can be measured through the use of fairly quick tasks, such as lexical decision (Aguasvivas et al. 2020; Brysbaert et al. 2016), meaning that a large quantity of items can be evaluated in a short amount of time. Hence, it comes as no surprise that vocabulary and other verbal ability tests are often used as a proxy for crystallized intelligence (Furnham & Chamorro-Premuzic 2006; Sánchez Sánchez and Arribas Águila 2016; Ziegler et al. 2012). This, however, poses a concerning issue, as "verbal ability" and "crystallized intelligence" are often conflated, when in reality some verbal tasks can have a significant fluid component. For instance, a common verbal task presents a sentence with a blank space —such as "*long* is to *short* what *tight* is to ____"— and requires the participant to fill in the gap with the appropriate word among an array of options —e.g., *wide*, *narrow* and *large*—. While the participant must know the meaning of the response option words in order to pick the correct one —which requires crystallized intelligence—, they must also be able to deduct the relationship between the initial pair of words and pick an option that follows the same pattern —which requires reasoning ability—. Similarly, and perhaps more importantly, crystallized intelligence is not just

limited to vocabulary knowledge; rather, it extends way beyond, to all possible types of acquired knowledge. This means that exclusively using vocabulary — or verbal— tasks as a measure of crystallized intelligence fails to include a significant portion of a person's knowledge, and hence a significant portion of crystallized intelligence. Therefore, other components of crystallized intelligence must be more deeply studied in order to properly understand the construct.

Another one of such components is that of general knowledge, defined as the ability to retrieve culturally relevant facts and information of a varied nature. Much like vocabulary size, it is also an aspect of crystallized intelligence that is mostly declarative in nature. However, unlike vocabulary size, it requires knowledge on proper nouns, dates and highly specific terms, which are normally not included in vocabulary size tests, and therefore taps on clearly distinct aspects of crystallized intelligence. General knowledge is also unique in that it covers a wide variety of topics —from biology and physics to art and history—, while being "shallow" enough that only a handful of items per field of knowledge is needed. Furthermore, general knowledge items can be responded fairly quickly, as they can be presented as a multiple-choice question that does not require any deep processing —either you immediately recognize the answer, or you do not recognize it at all—. Hence, it is a great candidate for research within crystallized intelligence, as it has the same key advantages that vocabulary size has —being culturally relevant and convenient to measure—, while still being differentiate enough to merit its own line of research.

Despite all these advantages, research on general knowledge is surprisingly scarce, at least as it relates to it being an aspect of crystallized intelligence. To our knowledge, only a handful of studies (Chamorro-Premuzic et al. 2006; Furnham et al. 2008; Furnham & Chamorro-Premuzic 2006) have explicitly drawn a relationship between general knowledge scores and measures of intelligence. Their findings reveal that general knowledge scores are strongly (r = 0.4 to 0.6) correlated with general IQ measures and, to a lesser extent (r = ∼ 0.3), to fluid reasoning measures. They also find that, as theorized by Ackerman (Ackerman 1996), personality measures are predictive of general knowledge scores, especially Openness. These studies, however, use intelligence measures such as the Wonderlic Personnel Test (Wonderlic Inc. 1999)

and Raven's Progressive Matrices (Raven 1965), which are designed to act as quick and convenient measures of intelligence. Because of this, both of these tests only provide general IQ scores, without delving deep into its subcomponents. Furthermore, while the Raven's Progressive Matrices test has traditionally been considered a general intelligence test (Arthur & Woehr 1993), recent research shows that it is only truly suited to measure logical reasoning skills, and that it does not act as a particularly precise indicator of general intelligence (Gignac 2015).

Because of this, the former only provides general IQ scores, without delving deep into its subcomponents, while the latter only provides measures of reasoning abilities. Therefore, while these studies are a fantastic steppingstone from which to start examining the relationship between general knowledge and other aspects of intelligence, further research is required to decipher how various aspects of intelligence interact with general knowledge.

Thus, the aim of the current study is to expand on these findings by examining the relationship between general knowledge and specific sub measures of fluid intelligence —logical reasoning, spatial skills, numeric abilities…—, as well as classical, verbal-based measures of crystallized intelligence. To that end, we designed a general knowledge questionnaire and had participants complete it alongside a series of intelligence tests measuring several various aspects of intelligence. We then computed linear regression analyses to identify which specific subcomponents of intelligence best predict general knowledge scores.

Similar to previous studies on general knowledge (Chamorro-Premuzic et al. 2006; Furnham et al. 2008; Furnham & Chamorro-Premuzic 2006), and in consonance with Cattell's intellectual investing theory (Cattell 1963), we expected to find that general IQ scores would be strong predictors of general knowledge scores. We also expected, however, that only certain subcomponents of intelligence would display a significant correlation with general knowledge scores. We specifically anticipated crystallized intelligence/verbal ability and reasoning measures to be strong predictors, but we also expected to find new subcomponents of intelligence to also be predictive of this kind of knowledge.

Methods

Participants

The sample was comprised of 90 participants (78 women and 12 men) of ages between 18 and 40 years old (M = 20.7; SD = 3.22), all of which were students at Nebrija University and spoke Spanish as their native language. They were compensated with 45€ for their participation.

Materials

Participants completed a general knowledge questionnaire —described first— and several intelligence tests —described below in completion order—. All the tests were completed on a computer, and hence their computerized versions were used.

General knowledge questionnaire

A subset of 120 items was extracted from a database (Buades-Sitjar, Boada, Guasch, Ferré, Hinojosa, Brysbaert, et al. 2021) comprised of over 1,300 items designed to measure declarative, general knowledge in over 35 different field of knowledge, such as history, art, biology, technology and physics. Each item is comprised of a question —e.g., "What do hertz measure?"— and four answer options —e.g., "Frequency", "Sound volume", "Voltage" and "Electric resistance"—. It also includes the pick-ratio of each response option, and links to Wikipedia articles where the answer can be confirmed. The database was originally normed using Spanish university students, meaning that the original sample and that of our study were similar enough for the norming to be applicable.

Only items with a correct response rate between 55% and 65% were selected as part of our questionnaire. The 120 items used in our questionnaire were randomly chosen out all the items from the original database that fit the criterion, making sure to select at least 2 questions from every field of knowledge.

Batería de aptitudes TEA (BAT-7) (Sánchez Sánchez & Arribas Águila 2016)

A general intelligence scale comprised of 7 subtests that measure specific aspects of intelligence. The subtests include the following:

Verbal (BAT-V)

32 items in 12 minutes. Participants are shown sentences such "*long* is to *short* as *tight* is to ____", and they must find which word, out of a given list, best fits the blank space. It evaluates not only vocabulary knowledge, but also the capacity to process analogies and relationships between words.

undefined>Spatial (BAT-S)/undefined>

28 items in 15 min. Participants are shown a die with symbols on each of its faces, as well as a 2D version of the same die with some of the symbols missing. They must find which symbol belongs in a specific face of the 2D die. It evaluates the capacity to mentally manipulate visuospatial information, both in two and three dimensions.

undefined>Attention and Concentration (BAT-A & BAT-C)

80 items in 8 min. Participants are shown one reference symbol and a row of other similar-looking symbols, and they must count how many times the reference symbol appears in the row. The test evaluates both speed (Attention) and accuracy (Concentration) of sensory processing.

Reasoning (BAT-R)

32 items in 20 min. Participants are shown a row of symbols following a logical pattern, and they must choose, among four options, which item follows the pattern. It evaluates the ability to draw inferences from visual information and to apply them.

Numeric (BAT-N)

32 items in 20 min. Participants are presented with various types of mathematical problems, such as simple algebraic equations, logical series of numbers

and tables and graphs from which they must extract information to answer questions. It evaluates the capacity to reason using numerical information.

Mechanical (BAT-M)

28 items in 12 min. Participants are shown drawings of "real life" scenarios where they must use their knowledge on basic physics principles to answer questions —no calculations or formulas are required—. It evaluates the degree of understanding of the mechanical principles behind forces, movement, and balance.

Orthographic (BAT-O)

32 items in 10 min. Participants are show four different real words, and they must identify which of them is incorrectly written. It evaluates knowledge on orthographic rules and vocabulary.

Cognitive assessment battery (CAB)

The CAB is comprised of a series of 17 short tests ($\sim$ 3 min each). Each of these measures a wide array of cognitive abilities, putting a heavy focus on executive functions. These are then used to obtain a general score, as well as five different subscores:

Perception (CAB-P)

Evaluates visuospatial and auditory processing, scanning and recognition.

Attention (CAB-A)

Evaluates sustained attention, divided attention, response inhibition and self-monitoring.

Memory (CAB-M)

Evaluates phonological and visual short-term memory, working memory and contextual memory.

Coordination (CAB-C)

Evaluates hand-eye coordination and speed of response to simple stimuli.

Reasoning (CAB-R)

Evaluates planning, processing speed and cognitive flexibility.

It should be noted that each of these subscores is not measured by one specific test or group of tests. Rather, different aspects of each of the 17 tests —such as response accuracy, speed, consistency, or the type of stimulus used— are used to calculate them, meaning that some of the tests contribute in some way to different subscores.

Raven's 2 progressive matrices (Advanced version) (Pearson 2019)

An extremely popular intelligence test in which participants are shown a matrix of visual symbols with one of them missing. The items in the matrix follow a logical pattern, and the participant must find it and choose, among a set of option responses, which of them best fits the blank space. While it is often used as a fast way to measure general intelligence, the test's focus is that of logical reasoning. The test is comprised of a total of 45 items, but it is automatically finished earlier if participants fail 6 items in a row.

Claves (Seisdedos 2004)

A reasoning test that combines both verbal and visual material. On the top side of the screen, participants are shown a series of words; on the bottom side, participants are shown a series of groups of symbols. Each symbol represents a unique letter, and each group of symbols represents one of the words on the top of the screen. Participants must, through logical reasoning and deduction, find which symbol represents a given letter. The test contains a total of 30 items to be solved in a maximum of 25 min.

Evaluación factorial de las aptitudes intelectuales (EFAI-4) (Santamaría Fernández 2005)

A general intelligence test that is comprised of 4 different subtests, in a similar fashion to the BAT-7. The four subscales are:

Verbal (EFAI-V)

22 items in 5 min. Some of the items resemble those of the BAT-V, where the participant must pick the correct word to complete a word analogy. It also includes items where a series of words are presented and the participant must pick the odd-one out. It evaluates vocabulary knowledge and the capacity to infer and apply analogies and relationships between words.

Numeric (EFAI-N)

25 items in 14 min. Similar to the BAT-N, it includes simple calculations and extraction of information from tables and graphs, as well as mathematical problems. It evaluates the ability to operate with numeric information.

Spatial (EFAI-E)

22 items in 7 min. Participants must perform various visuospatial tasks, such as finding which piece fits in a given puzzle space or which shape is hidden behind a certain figure. It evaluates visuospatial ability, but with a focus on perspectives and interactions between figures.

Reasoning (EFAI-R)ed>

25 items in 11 min. Similar to other reasoning tasks, participants are presented with series of figures following a logical pattern that they must complete. However, the patterns here are comprised of either watches or body figures, requiring unique kinds of processing.

Procedure

Participants were divided in four different groups for data collection. The collection process was the same for all groups, and this division was purely for the purpose of convenience of scheduling. Each group completed the data collection along three sessions, each taking place the day right after the previous one. In the first session, participants completed the BAT-7; in the second session, they completed the general knowledge questionnaire, the CAB and the Raven's Progressive Matrices; in the third session, they

completed the CLAVES and the EFAI-4. Participants were rewarded after completing the last session.

Data analysis

Prior to performing any actual analysis, the scores of each test and subtest were converted into Z scores. These transformations were performed using the parameters of the original scales used in the validation process of each test, rather than on those of our own data. The resulting Z scores were analyzed at two different levels of specificity: general test scores and specific test scores.

In the general test scores analyses, we computed a linear regression analysis using the general knowledge scores as the predicted variable and the general intelligence scores of each test as the predictor variables. We used the R function *stepAIC* from the MASS library (Venables & Ripley 2002) in order to find the most efficient model —i.e., one that could explain the greatest amount of variance with the least number of variables.

In the specific test scores analyses, we first computed one linear regression analysis per test, using the specific sub-test scores as the predictor variables — e.g., for the BAT-7, the predictor variables were the Verbal, Mechanical, Orthographic, Numeric, Reasoning, Spatial, Focus and Attention—. Just like in the previous analysis, we used the stepAIC function to find the most efficient models. After performing the analysis for every test, we repeated the same process using the most powerful sub-test predictors of each test —i.e., the sub-tests that remained in each model—.

Results

Table 1 displays the score means and standard deviations for the general knowledge and all intelligence tests, as well as their Pearson's correlation coefficient. All correlations were statistically significant. On average, participants correctly answered 49.35 (SD = 9.21) of the 120 general knowledge questions, which amounts to a 41.12% (SD = 7.67%) correct response rate. In the original study (Buades-Sitjar et al. 2021a, b), the average correct response ratio

was 50%, meaning that our sample scored somewhat lower than the original sample.

Table 2 displays the stepwise decomposition of the significant general test scores, as well the significant subscores of each test. Hereunder, we indicate which test and subtest scores were rejected due to either not being significant predictors of general knowledge by themselves, or due to losing significance once paired with other predictor variables.

General test scores

Even though all general test scores were significant predictors of general knowledge when included in the model as the only predictors, they all ceased to be significant once the BAT-7 was added into the model. The beta coefficients for the final model were 49.99 for the Intercept and 6.7 for the BAT-7 scores. The model's adjusted R^2 was 0.32.

Specific subtest scores

BAT-7

Except for the Concentration score, all of the BAT-7 subscores acted as significant predictors of general knowledge when each of them was included in the model by themselves. However, as the rest of the variables were added into the model, only the Orthography, Numerical and Mechanical subscores remained significant, while the Verbal, Spatial, Attention and reasoning subscores lost their predictive power.

The beta coefficients for the final model were 51.52 for the Intercept, 2.33 for the BAT-Orthography score, 2.63 for the BAT-Numeric score and 3.21 for the BAT-Mechanical score. The model's adjusted R^2 was 0.42.

CAB

Except for the Attention score, all of the CAB subscores acted as significant predictors of general knowledge. However, only the Memory subscore remained significant as the rest of the variables were added into the model, while the Perception,

Table 1 Means, standard deviations and correlations of test scores

Test	M	SD	1	2	3	4	5
1. General knowledge	49.35	9.21					
2. BAT-7	98.56	11.87	0.58***				
3. CAB	508.77	104.7	0.31**	0.42***			
4. Raven	91.84	12.74	0.41***	0.66***	0.28**		
5. Claves	104.47	15.37	0.23*	0.47***	0.31**	0.43***	
6. EFAI-4	93.95	12.45	0.39***	0.46***	0.28**	0.44***	0.36***

$*p < 0.05$, $**p < 0.01$, $***p < 0.001$

Table 2 Stepwise decomposition of the models, including significant predictors only

	Step 1		Step 2		Step 3	
Predictor	β	R^2	β	R^2	β	R^2
General Scores						
Intercept	49.99	0.32				
BAT-7	6.7					
BAT-7						
Intercept	51.48	0.15	50.76	0.31	51.52	0.42
BAT-O	3.98		2.63		2.33	
BAT-N			3.61		2.63	
BAT-M					3.21	
CAB						
Intercept	47.86	0.12				
CAB-M	5.82					
EFAI-4						
Intercept	51.53	0.08	52.73	0.19		
EFAI-N	3.54		2.81			
EFAI-V			3.68			

Coordination and Reasoning subscores lost their predictive power.

The beta coefficients for the final model were 47.86 for the Intercept and 5.82 for the CAB-Memory. The model's adjusted R^2 was 0.12.

EFAI-4

Except for the Reasoning subscore, all the EFAI-4 subscores acted as significant predictors of general knowledge. However, only Verbal and Numeric subscores remained significance as the rest of the variables were added into the model, while the Spatial subscore lost its predictive power.

The beta coefficients for the final model were 52.73 for the Intercept, 2.81 for the EFAI-Numeric and 3.68 for the EFAI-Verbal. The model's adjusted R^2 was 0.19.

All subscores

When performing an analysis including the remaining significant subscores from each test, only those from the BAT-7 test —BAT-Ortohographic, BAT-Numerical and BAT-Mechanical— remained significant, while the CAB-Memory, the Raven, The Claves and the EFAI-Verbal and EFAI-Numeric ceased to be significant. Therefore, the final model remained identical to the BAT-7 scores model (Intercept = 51.52, BAT-Orthography = 2.33, BAT-Numeric = 2.63, BAT-Mechanical = 3.21; adjusted $R^2 = 0.42$).

Discussion

While research on fluid intelligence and its different components has been extensive (Bart et al. 1980; Langdon and Warrington 2000; Liang et al. 2020), research on crystallized intelligence has been severely limited due to the methodological constrains associated with its measuring. The only component of this type of intelligence that has been thoroughly studied is vocabulary size (Aguasvivas et al. 2020; Brysbaert et al. 2016), which has resulted in the common misuse of "crystallized intelligence" and "verbal ability" as synonyms. This poses a considerable problem for two reasons: first, because verbal ability tests often include clearly fluid tasks; and second, because this conflation has also led to verbal ability being often used as the only measure of crystallized intelligence (Furnham and Chamorro-Premuzic 2006; Sánchez Sánchez & Arribas Águila 2016; Ziegler et al. 2012), excluding all its other components. The current study attempted to address these issues by exploring how a different component of crystallized intelligence, general

knowledge, relates to all other components of intelligence. To that end, we had participants complete a general knowledge questionnaire, as well as several different intelligence tests, and computed linear regressions in order to find which aspects of intelligence are the best predictors of general knowledge.

When using general intelligence test scores as predictors of general knowledge, we found that the BAT-7 test had the strongest predictive power. In fact, even though all other tests acted as significant predictors of general knowledge when included in the model by themselves, they all lost their predictive power once the BAT-7 entered the model. This indicates that all the tests used in this study share some sort of common factor that explains a specific portion of the variance in general knowledge scores, and that the BAT-7 scores are better predictors of said factor. In regard to how the BAT-7 better predicts it, there are two possible explanations. The first one is that, even though the cognitive abilities measured by the other tests have a direct positive impact on general knowledge as shown by each individual analysis, the BAT-7 could act as a more precise predictive measure of said cognitive abilities, which would cause all other tests to become redundant and lose their predictive power. The second explanation is somewhat opposite to the first one, and is that the BAT-7 measures unique aspects of intelligence that have a more direct impact on general knowledge scores than those common to the rest of the tests. Spearman (Spearman 1904) suggested that there is a general intelligence (g) factor that explains a common variance of all intelligence test scores, and more recent studies also find that different components of intelligence are often correlated, and people with higher scores in one aspect of intelligence tend to score higher in other aspects as well (Ackerman et al. 2001; Mix et al. 2016; Nusbaum & Silvia 2011). Hence, it is possible that the predictive power of tests such as Raven's Progressive Matrices is incidental, stemming from their scores being correlated to the unique skills measured by the BAT-7, which would have a direct influence on general knowledge. Our results back up this explanation. First, even though all test scores were significantly related to each other, the correlations were far from being perfect, most ranging from low to moderate-high. This means that, even though there was a common factor measured in all the different tests — the g factor—, each of them also measured unique

aspects of intelligence. Second, and most crucially, after combining all subtest scores into one model, only the BAT-Orthography, BAT- Numerical and BAT-Mechanical remained as significant predictors. Incidentally, the types of intelligence measures by these tests happen to not by measured by the other tests in used in our study. Therefore, there is strong evidence to suggest that the BAT-7 better explains general knowledge scores by virtue of measuring aspects of intelligence that are more tailored to this particular kind of knowledge, while the predictive power of the rest of the tests comes from them being correlated to these unique aspects through the g factor.

When it comes to the BAT-Orthography, a notable aspect of this test is its explicitly crystalized nature, as it requires the participant to tap on their already existing orthographic knowledge to identify which of the four written words is not spelled properly. In fact, even though the Spanish language is known for having considerably transparent orthographic rules, most of the incorrectly written words that the participants need to identify differ from their properly written form in that there is either an excess/absent H, or that there has been a swap between the G/J, LL/Y or V/B consonants —which is Spanish share the same sound—. Coincidentally, these happen to be of the few aspects of Spanish orthography that do not normally follow specific rules, meaning that the possibility of applying the orthographic rule to obtain the correct response —which would be a more fluid ability— is missing. Hence the only way to recognize the incorrectly written word is by explicitly remembering how that specific word is spelled. Therefore, it is likely that the predictive power of the BAT-Orthography stems from it measuring and individual's ability to retrieve highly specific information from long-term memory, a crucial skill in a general knowledge questionnaire such as ours. Interestingly enough, the CAB-Memory, which is also memory-focused, did not make it into the final model. The most likely reason is that the CAB-Memory is mainly concerned with short-term and working memory, rather than with retrieving information from long-term memory.

The BAT-Numeric included three kinds of numerical tasks: simple algebraic equations, logical series of numbers and solving problems by extracting information from graphs and tables. Considering the nature of these tasks, the BAT-Numeric might predict general knowledge scores in several different ways. The first is

a more indirect one: since most STEM-related topics require having a solid numerical ability, it is likely that people who are highly knowledgeable in STEM-related topics would also score higher in a numerically oriented test such as the BAT-Numerical. Seeing as our general knowledge questionnaire includes questions from several STEM fields such as biology, medicine, physics and chemistry, their STEM knowledge could have aided them both in obtaining a higher general knowledge score and a higher BAT-Numeric score. The BAT-Numeric also asks participants to process information in unique ways that might be helpful in non-STEM fields such as literature or history. First, while most tests only present a handful of relevant pieces of information at a time, the BAT-Numerical presents participants with large tables and graphs, full of often redundant and useless information. Participants must be able to identify the relevant pieces of information to the problem at hand while ignoring the irrelevant bits. Similarly, literature and history textbooks often present us with large walls of text from which we must summarize the most important bits in order to remember all the information we need. Hence, the ability to select relevant and ignore irrelevant information is likely to be of aid at acquiring knowledge in said areas. In the same line, being able to organize information into graphs and, tables and timelines, as well as being able to interpret them, greatly helps at absorbing and retrieving said information. Therefore, people with such skill are also likely to have an easier time acquiring and retrieving declarative knowledge. Finally, the BAT-Numerical also requires participants to juggle information from very different modalities. Even though the main stimuli are numerical, problems are presented in a verbal manner, —e.g., "Considering the following graph, what was the average price increase in the seven months prior to July?"—, and information is visuospatially organized through tables and graphs, requiring participants to seamlessly translate one type of information into the other. Similarly, historical events and literature and philosophy movements are often presented alongside numerical dates, which are then organized in mental timelines, and STEM concepts often require translating a verbal explanation or a numerical equation into visual imagery. Hence, the ability to operate with various types of information and to convert one into the other is likely to be of great aid when acquiring certain kinds of knowledge.

The final significant predictor of general knowledge scores was the BAT-Mechanical test, where participants are presented with a "real life" scenario and must use their knowledge on basic mechanical principles to guess how the scenario will play out. For instance, participants might be shown a picture of two houses, one with a flat roof and one with a pointed roof, and then be asked which house would better withstand a violent snowstorm —in this case, the one with the pointed roof—. Solving these kinds of problems requires solid reasoning skills, as one starts with a set of premises —the pictures provided by the test and the mechanical principles relevant to the scenario— and must figure out the end result of their interaction. However, the kind of reasoning required in this situation differs significantly from that of other reasoning tests such as Raven's Progressive Matrices, Claves, the CAB-Reasoning or even the BAT-Reasoning. These tests require inductive reasoning, where participants are presented with series of items that follow a specific rule and they must figure out what rule it is. Meanwhile, the BAT-Mechanical requires deductive reasoning, as participants start with a given scenario and must apply a mechanical rule to predict the end result. Such kind of reasoning is critical in STEM-related topics, as understanding mechanical principles, cause-consequence relationships and applying given sets of rules to new situations is key to solving problems in these fields. However, it is also particularly useful when studying topics such as history or philosophy, as historical events and currents of thought are often a direct consequence of other previous historical events and currents of thought. This would help in comprehending the historical context of any given happening, which would be of much more aid at remembering related information than simple memorization.

Our study offers new insights into general knowledge, a scarcely explored component of crystalized intelligence. First, it expands on the findings from previous studies on general knowledge and intelligence (Chamorro-Premuzic et al. 2006; Furnham et al. 2008; Furnham & Chamorro-Premuzic 2006), showing that it is not general IQ scores as a whole that predict general knowledge, but rather specific aspects of intelligence that are either directly or indirectly measured by IQ. It also lends support to Cattell's theory of Intellectual Investment (Cattell 1963, 1967), showing that a higher fluid intelligence predicts a

higher crystallized intelligence. The fact that only certain aspects of intelligence were predictive of general knowledge also adds depth to his theory, suggesting that specific kinds of crystallized intelligence will benefit more from specific kinds of fluid intelligence. For instance, the skills that support the acquisition of declarative general knowledge are likely to differ drastically from those that support learning a more procedural task, like riding a bike. In that task, stimulus perception, sustained attention and reaction speed are likely to be more beneficial than orthographic knowledge or numeric ability. Therefore, a test such as the CAB, which focuses more on executive functions, would likely be more predictive of the degree of proficiency at riding a bike.

These conclusions also fit Ackerman's theory on the influence of personality and personal interests on the fluid-crystallized intelligence interaction (Ackerman, 1996). He suggested that personality and interests act as a driving force that influences how much effort is invested in the process of acquiring knowledge. Since the acquisition of certain kinds of knowledge often requires specific fluid skills, a person with a strong interest in a certain field of knowledge would inevitably end up developing said skills. For instance, someone with a strong interest in history will likely invest a considerable amount of time into acquiring history knowledge. However, they would eventually run into the problem of being exposed to excessive amounts of information, which would lead them to develop the skill to select and organize the most relevant bits in tables or timelines. This would, in turn help them keep acquiring knowledge, as it would give them the tools to process said excessive amount of information. Hence, the relationship between fluid and crystallized intelligence would be an interactive process fueled by non-ability factors, where personal interests would lead to wanting to acquire knowledge, which would lead to the development of certain set skills that facilitate that acquisition.

Our study is not without limitations, however. First, even though both our sample size and the number of items in our general knowledge questionnaire are relatively large, it still lacks the validity that a macrostudy such as Brysbaert et al. (2016) or Buades-Sitjar et al. (2021a, b) has. The time and resources associated with using tests that include measures on various components of intelligence severely limits the ability to conduct an experiment

of such a gargantuan size. Yet, we consider our study to be a solid next step in the topic, as it expands on previous research on the matter (Chamorro-Premuzic et al. 2006; Furnham et al. 2008; Furnham and Chamorro-Premuzic 2006), while suggesting that it would be worthwhile replicating it at a much larger scale. Our study also cannot truly confirm the exact nature underlying the interaction between general knowledge and all other relevant components of intelligence. While we consider our proposal based on the theories by Cattell (Cattell 1963, 1967) and Ackerman (Ackerman 1996) to make strong theoretical sense, experimental studies that can confirm this interests-fluid skills-knowledge dynamic are still required.

In conclusion, our study provides new information on an underexplored aspect of crystallized intelligence, general knowledge, studying its relationship with other aspects of intelligence. It also provides evidence supporting the theory of Intellectual Investment formulated by Cattell (Cattell 1963, 1967), all the while deepening it by showing that only specific components of fluid intelligence facilitate the acquisition of certain aspects of crystallized intelligence. Finally, it opens up new avenues for research that can both confirm and deepen the findings and conclusions of this study.

Declarations

Conflict of interest   We have no known conflict of interest to disclose.

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