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A Demonstration of The Positive Manifold of Cognitive Test Inter-correlations, and how it Relates to General Intelligence, Modularity, and Lexical Knowledge

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Abstract

Widely recognized in differential psychology, but less so in cognitive science, the positive manifold is the phenomena of all cognitive tests inter-correlating positively. Frequently demonstrated in people, it can also be observed in non-human species. With 217 Ecuadorian adult participants, who performed 11 cognitive tests, we show that all 55 pairwise inter-correlations are positive, and of large magnitude. Additionally, factor analysis revealed a single underlying general, or *g* factor, often identified as general intelligence. This robustly replicates the positive manifold in a non- WEIRD (Western, Educated, Industrialized, Rich, Democratic) context. We further demonstrate that tests of lexical knowledge, such as word pronunciation, have particularly high loadings on *g*. We explore explanations for the positive manifold, and the implications for understanding the mind as being composed of independent cognitive processing modules. We propose that the positive manifold reveals a neglected but important role of lexical-conceptual knowledge in high-level, top-down, domain-general cognitive processing.

Keywords: intelligence; modularity; g factor; process overlap theory; crystalized ability; mental lexicon; vocabulary

Introduction

The Positive Manifold

When sufficiently diverse groups of people are tested with multiple cognitive tests it is found that all of the test scores correlate positively (Jensen, 1986). That is, if a particular individual scores highly on one test, they are also likely to have scored highly on the other tests. The array of only positive associations is known as the positive manifold of correlations. Furthermore, the correlation values, in addition to being always positive, are generally of a large magnitude. This has been taken to indicate a general factor that contributes to all human cognitive processes.

The presence of the positive manifold in large data sets of cognitive test performance means that factor analysis can always be used to extract a single factor. That factor is the general factor, or simply *g*. The concept of a "general intelligence", that contributes to all cognitive functions has been an attractive and simple explanation for *g* (e.g., Carroll, 1991). Furthermore, in humans, *g* is associated with a range of biological factors including nerve conduction velocity (Reed, Vernon, & Johnson, 2004), and brain size, which also appears to have a genetic basis (Lee et al., 2019). The positive manifold and *g* are also observed in other species. This includes non-human primates and rodents, where there is reliable evidence for *g*, and that it also positively correlates with brain size (Burkart, Schubiger, & van Schaik, 2017). These factors further support the concept of *g* as being a fundamental feature of neurocognitive processing.

Modularity

Nevertheless, although *g* is a statistical reality, across species, and is associated with a range of biological features, its actual physiological basis in the brain is elusive (Haier et al., 2009). Furthermore, the very concept of a general intelligence appears to be inconsistent with the concept of modularity of cognitive functions, such as that proposed in the classic theoretical work on human cognitive architecture provided by Fodor (1983).

This contradiction between modularity on the one hand, and general intelligence on the other, is particularly problematic in the field of cognitive neuropsychology, in which modularity is a core assumption (Coltheart, 2001). That assumption underlies the methodology of double dissociation in which independence of cognitive process are ascertained by comparing patterns of observed cognitive impairments across neurological patients. The cognitive neuropsychological approach has been fruitful in identifying specific cognitive processes, particularly in regard to visual cognition, which appear to be independently susceptible to brain lesions. Consistently localizable areas of the brain are associated with impairments of recognition of very specific classes of stimuli, such as common objects, faces, places, or words, suggesting a substantial degree of both cognitive and neurobiological modularity in the human brain (Martinaud et al., 2012). Some theorists have gone as far to propose that the human mind is 'massively modular' (e.g., Carruthers 2006). How then can the accounts of general intelligence and of cognitive modularity be reconciled, given the reality of the positive manifold?

Process Overlap Theory

A recent suggestion that has been gaining support is known as Process Overlap Theory (Kovacs & Conway, 2016). This draws on studies that have suggested that *g* can be (nearly) perfectly explained by normal human variation in working memory ability (Colom et al., 2004). A similar argument has been put forward for fluid intelligence being the basis of *g*, which is conceptualized as reasoning ability in novel situations. Statically derived latent variables of fluid intelligence also (almost) perfectly predict *g* (Kan et al., 2011). A third version of this approach asserts that 'cognitive control', defined in terms of executive functions, is the basis of *g* (Chen et al., 2019), and hence the positive manifold.

What these theories all have in common is that they argue that domain-general processes are related to the positive manifold. Process Overlap Theory which embraces these approaches, argues that various overlapping domain-general cognitive control functions produce a bottleneck on information processing. That limitation then influences all task performance.

This theory is supported by cognitive neuroscience, from which several domain-general brain systems have been proposed. The different theories all propose more or less the same network of brain regions in the frontal lobes and posterior parietal lobes, which seem to be recruited independently of task content. Typical of these is the Multiple-demand System (Duncan, 2010), proposed as being a domain-general processing system that implements sub-tasks to achieve goals and hence the coordination of fluid, intelligent action. The Multiple-demand System is argued to be the physiological basis of fluid ability and various executive functions, including inhibition, attention and working memory (Camilleri et al., 2018). It does this, supposedly, through acting as a domain-general processing hub for an otherwise largely modular neurocognitive system (Kovacs & Conway, 2016). This theory can, for the most part, explain the positive manifold, without invoking a singular general intelligence factor. It does this by arguing that all tasks require some form of the Multiple-demand System, even if it just to do with focusing on the task, or storing a verbal response to guide an answer to a question.

Lexical Ability

There are nevertheless some features of the positive manifold which are not so clearly explained by invoking high-level cognitive control mechanisms. In particular, the fact that crystalized intelligence, such as a person's vocabulary or their general knowledge, typically predicts more variation in *g* (i.e., it has overall stronger correlations with other, non-verbal cognitive tasks) than any other tests, including laboratory tests of working memory or fluid intelligence (Gignac, 2006). Crystalized intelligence is by definition highly dependent on education and culture, and by definition fluid intelligence is minimally influenced by education and culture. Crystalized intelligence is mainly composed of verbal ability, and knowledge, such as vocabulary, but it is the latter factor that is most closely linked to *g* (Schipolowski, Wilhelm, & Schroeders, 2014). Simply put, a person's lexicon, as measured by their vocabulary, is a better predictor of their general intelligence than any other cognitive measure (Crawford et al., 1989; Jensen, 2001). As an example from clinical sciences, word pronunciation, with assessments such as the National Adult Reading Test (NART), is the principle method used to assess premorbid intelligence in patients with brain damage. This is because it is very highly correlated with intelligence test scores (Crawford et al., 1989), yet resistant to cognitive impairment. For explanations of the *g* factor which invoke high-level fluid mechanisms, this is the 'elephant in the room'. Why should vocabulary tests, which appear rather effortless to perform, be so highly *g* loaded, if the explanation for the *g* factor is based on effortful fluid processing?

The Current Study

We had two principal objectives. Firstly, to demonstrate the positive manifold, given its implications for interpreting theories in cognitive science that involve the concept of modularity. Further as most of the research on this has come from WEIRD countries, i.e., Western, Educated, Industrialized, Rich and Democratic (Henrich, Heine, & Norenzayan, 2010), we wished to assess the phenomenon in a non-WEIRD population. A demonstration here is also useful because it has didactic value, being much easier to conceptualize than a reified latent variable such as general intelligence. We therefore report a study of the positive manifold from 11 different cognitive tests completed by a large sample of Ecuadorian adults. Eight of these tests were from a standard intelligence test and together would be expected to produce a psychometric *g* if factor analyzed together. However, we also included three other tests that involve minimal active fluid processing, and measure acquired lexical knowledge of language. The aim is not to perform statistical null-hypothesis tests, but to investigate whether we could reproduce the strong *g* loadings that are frequently observed for lexical and verbal tasks. In addition, to explore how the contribution of lexical tests fits with theories of the relationship between *g* and domain-general fluid ability, and how the relations can be reconciled with concepts of cognitive modularity.

Method

Cognitive Tests Used

Eight different tasks that are part of the Wechsler Adult Intelligence Scale 4th Edition (WAIS-IV) Spanish version were used (Wechsler, 2012), all of which have substantial *g* loadings (Canivez & Watkins, 2010). These were Block Design (a manual visuospatial task using red and white colored blocks), Similarities (a verbal test requiring the identification of an abstract concept that links two different words), Digit span (a test of repeating aloud sequences of digits presented aurally), Digit sequencing (a test of orally sequencing strings of numbers delivered aurally), Arithmetic (a test mentally conducting calculations delivered aurally), Information (a test of general knowledge), Coding (a manual psychomotor test of transcribing abstract symbols), and Picture completion (a test of reporting the missing parts from a series of color drawings). Most of these tests are scored on accuracy, however, Block design involves extra points for fast performance, and Coding is scored solely as the number of symbols correctly transcribed within 2 minutes. Evidence of the validity of the WAIS-IV as a measure of intelligence in Ecuador has been demonstrated by its large correlation with academic achievement (Pluck et al., 2016).

We also used three tests of lexical ability. As this research was conducted in Ecuador, South America, these are all tests of Spanish lexical information. Importantly, all three tests appear to place very low demands on executive processes.

The first was the Spanish Lexical Decision Task (SpanLex) in which participants are presented with three words, in which only one is a real word and the others are realistic looking nonwords, with the task being to pick the real word. Evidence for the validity and reliability of this as a measure of vocabulary, in Ecuador, is provided in Pluck (2020). The second lexical task was the Word Accentuation Test (WAT). This involves pronouncing low frequency words in which the word-stress information is not shown. It is equivalent to pronouncing English words that have irregular spellings, such as in the National Adult reading Test (NART; Crawford et al., 1989). Evidence for the reliability and validity of the WAT has been previously demonstrated in an Ecuadorian sample (Pluck et al., 2018). The third test was the Stem-Completion Implicit Reading Test (SCIRT). This tests semantic knowledge through a form of confrontation naming. However, multiple primes (visual, phonemic and semantic) are given to minimize the need for strategies in the search of the lexicon for the word form. There is previous evidence from an Ecuadorian sample for the validity and reliability of this as a measure of crystalized semantic-lexical knowledge (Pluck, 2018).

Participants and Procedure

217 adult participants were assessed with all of the cognitive tests. All were Spanish speakers. Of the full sample of 217 participants, 118 (54%) were female and the mean age was 31.1 (SD = 16.7). The age range was from 17 to 93. Due to the wide age range, all raw cognitive test scores were adjusted for age, by entering them individually into linear regressions as dependent variables, with age as an independent variable, and saving the residuals. The mean years of formal education of the sample was 13.8 (SD = 3.1, range 2 – 26). The data was collected in four different Ecuadorian cities (Quito, n = 137; Riobamba, n = 30; Guayaquil, n = 30; Manta, n = 20). The participants identified as mestizo (n = 166), white (n = 19), indigenous (n =15), black (n = 12), or other (n = 5).

Each participant was interviewed in one-to-one test sessions with a psychologist. All participants gave written informed consent and the protocol had approval from an appropriate research ethics committee.

Results

The age-adjusted scores, not raw scores, were used in all analyses. As a first step, Pearson correlation r values were calculated for each pair of the 11 different cognitive tests (55 different pairs). As predicted, this produced a positive manifold in which all 55 correlations were positive and statistically significant at $p < .001$ (two-tailed). In addition, all 55 r values would be considered qualitatively large effects by a standard definition for individual differences research (Gignac & Szodorai, 2016).

This positive manifold is shown in Table 1. The diagonal in this matrix has been used to show the mean correlation of each of the 10 different cognitive tests with the cognitive test in question. For example, of the correlations of Block design with each of the other ten tests, the r values ranged between .37 and .60, with a mean of .55.

The strong inter-correlations shown in Table 1 suggest that a g factor will be extracted with factor analysis. Indeed, in the next step we used principal axis factoring with all 11 cognitive tests and found only a single factor, with an eigenvalue of 5.92, which explained 54% of the variance. Factor loadings are shown in Table 2. The highest loading was .78 for the SCIRT test, a measure of semantic word knowledge. In fact, the highest four factor loadings (i.e., the correlations with the g factor) were for tests that would be considered to rely substantially on crystalized ability, that is, tests of word or general knowledge. In contrast, the five tests with the lowest factor loadings would all be considered tests of fluid ability in a general sense, as performance is not obviously linked to any acquired knowledge. This emphasizes the point made in the Introduction: knowledge-based measures appear to be particularly associated with the psychometric g factor of cognitive test performance.

Nevertheless, this could be because four of the tests clearly measure the contents of mental lexicons in some way (SCIRT, WAT, Similarities, SpanLex), and this commonality could potentially drive the association and overly weight lexical knowledge in the extracted latent g factor. To test this, the factor analyses were repeated, but only including one lexical test in each set, plus the 7 non-lexical WAIS-IV tasks. The resultant factor loadings are shown in Table 2. When the SCIRT was analyzed with the 7 non-lexical tasks, again only one factor was extracted, with an eigenvalue of 4.30, explaining 54% of the variance. And again, the SCIRT had the highest loading on that factor, in fact the rank order of the different cognitive tests is very similar to the previous factor analysis with all 11 tests.

When the WAT was analyzed in this way, it was the second highest loaded on the single extracted factor (eigenvalue = 4.23, variance explained = 53%). For the Similarities test, that was found to be the highest loaded on the single general factor extracted (eigenvalue = 4.30, variance explained = 54%). So far, the lexical tasks have been shown to be highly g loaded, even when none of the other tests that they were factor analyzed with were lexical. For the SpanLex, the lexical decision task, this was no so highly loaded, having only the fourth highest rank on the extracted single factor (eigenvalue = 4.20, variance explained = 53%). Nevertheless, it had higher g loading than tests of working memory (Sequencing) and visuospatial processing (Block design), among other fluid ability tests.

Table 1: Matrix of correlation *r* values for the intercorrelations of the 11 cognitive tests, with the mean *r* value for each test given in bold in the diagonal

	1	2	3	4	5	6	7	8	9	10	11
1. Block design	**.55**										
2. Similarities	.59	**.59**									
3. Digit span	.37	.52	**.43**								
4. Digit sequencing	.55	.56	.57	**.53**							
5. Arithmetic	.57	.61	.48	.59	**.57**						
6. Information	.51	.63	.46	.58	.63	**.58**					
7. Coding	.57	.58	.32	.48	.55	.54	**.54**				
8. Picture completion	.55	.66	.38	.50	.60	.48	.54	**.52**			
9. SpanLex	.59	.48	.41	.49	.50	.61	.59	.40	**.54**		
10. Word accentuation	.55	.56	.42	.52	.59	.63	.66	.49	.68	**.58**	
11. SCIRT	.60	.67	.40	.45	.57	.72	.57	.60	.61	.66	**.59**

Discussion

Our results clearly replicate the positive manifold, with all 55 inter-correlations being positive, statistically significant, and qualitatively large effects. Although this is a recognized replicable effect, we point out that we have done so in a non-WEIRD country (Henrich et al., 2010). A secondary aim was to explore the role of lexical tasks in the positive manifold, and implications for conceptualizations of the mind as being modular.

Looking first at the positive manifold represented in Table 1. The highest mean correlations for any tests, at mean $r = .6$, were those that would be considered to be of crystalized knowledge, these were the SCIRT and the WAIS-IV Similarities test. Both of these require knowledge of the meanings of words. The tests with next highest mean correlations would also be considered of crystalized ability, the WAT and the WAIS-IV Information test, assessments of lexical word pronunciation and general knowledge, respectively.

Given the high level of inter-correlations in general, it is not surprising that in each factor analyses performed, only a single, general factor emerged. And as expected, lexical tasks were very highly loaded on the derived *g* factors. This held even when there was only a single lexical test included, suggesting that the lexical tests were all independently highly *g* loaded. This replicates previous research that has shown that lexical knowledge is very high on *g* (Crawford et al., 1989; Gignac, 2006; Jensen, 2001).

The question is, why should relatively simple tests of word knowledge be the best predictors of *g*, often taken to be general intelligence? Particularly considering theory that *g* is said to be a consequence of domain-general cognitive processes such as working memory (Colom et al., 2004). Here we briefly review some explanations that have previously been made for this phenomenon.

One explanation is that language processing does in fact require domain-general processing, such as abstraction of meaning when deciding how words are similar (Chen et al., 2019). However, this explanation may be specific to particular tasks such as the WAIS Similarities test, which superficially appears to be about declarative knowledge but actual has a substantial fluid reasoning component (Isingrini & Vazou, 1997).

An alternative explanation is provided by the theory that the *g* factor is due to working memory, which could be argued to have a unique role in internally representing task goals or task monitoring (Colom et al., 2004). Working memory would then be involved in performance of any task, even simple word-based tasks. Theoretically this is supported by assumptions that semantic memory is accessed via short-term memory storage (Cerone & Pluck, 2021). Given these assumptions, a reasonable explanation could be that the short-term/working memory contents drive the retrieval of crystalized declarative knowledge and use it to feed fluid reasoning, thus determining the fluid-crystalized duality that can be observed through the positive correlations expressed by the *g* factor.

This may be a partial explanation for why the WAIS-IV similarities subtest was highly *g* loaded, and perhaps also for the SCIRT, which despite the various primes given to aid retrieval, must still involve actively searching semantic storage. However, can it explain why pronunciation of unaccented or irregular spelled words is so highly loaded? To be pronounced correctly, such words have to be read through a lexical route, not through a more attention-demanding grapheme-phoneme conversion process. Indeed, lexicon-based word pronunciation feels rather effortless, and experimental evidence supports this. Increasing cognitive load actually improves performance on irregular word pronunciation, presumably because the increased load impedes the competing grapheme-phoneme conversion route, and indirectly biases towards the more appropriate lexical route (Paap & Noel, 1991). Further evidence is that damage to the brain's frontal lobes, and thus the proposed Multiple-demand System, appears to impair executive functions, without any effect on lexical word pronunciation

Table 2: Factor loadings for the full set of 11 cognitive tests, as well as each lexical test (in bold) analyzed with the 7 non-lexical tests from the WAIS-IV, all shown in rank order

All 11 tests		SCIRT + 7		WAT + 7		Similarities + 7		SpanLex + 7	
SCIRT	.78	**SCIRT**	.78	Arithmetic	.77	**Similarities**	.78	Arithmetic	.76
WAT	.77	Arithmetic	.77	**WAT**	.75	Arithmetic	.76	Information	.74
Information	.76	Information	.75	Information	.73	Information	.73	Coding	.70
Similarities	.75	Block design	.68	Coding	.71	Coding	.68	**SpanLex**	.70
Arithmetic	.74	Coding	.68	Sequencing	.67	Block design	.68	Block design	.68
SpanLex	.73	Picture	.64	Block design	.65	Sequencing	.66	Sequencing	.67
Coding	.70	Sequencing	.64	Picture	.60	Picture	.65	Picture	.60
Block design	.67	Digit span	.53	Digit span	.53	Digit span	.54	Digit span	.54
Sequencing	.64								
Picture	.62								
Digit span	.53								

(Bright, Jaldow, & Kopelman, 2002). Working memory or other executive influences on word pronunciation cannot therefore explain why tests such as the WAT or the NART are strongly represented in the positive manifold, and hence the *g* factor.

The other main proposition to explain why crystalized ability associates so highly with general intelligence is known as *investment theory* (Cattell, 1987). This argues that fluid ability, although itself culturally independent, allows people to learn lots of different skill and knowledge sets, and it is this culturally acquired information, including the mental lexicon, that yields crystalized intelligence. Or another way to put it, people with better domain general fluid ability learn more. Cattell (1987) argued that any associations between fluid reasoning skills and crystalized ability such as vocabulary are due to the effect of the former on the latter, but not vice versa.

Although undoubtably domain-general processes such as working memory are very important in language learning, why a consequence of domain-general processing should be more highly associated with *g* than the processes themselves is not clear. Furthermore, as language learning will also involve substantial non-*g* variation due to environmental factors (e.g., education), any effect of *g* via fluid processing would be attenuated.

A straightforward interpretation of investment theory thus would suggest that highly fluid processes such as working memory would be directly, and more strongly, linked to *g* than lexical knowledge which is apparently an indirect and impure measure of *g*. There is therefore no clear explanation of why lexical knowledge, such as vocabulary, or word pronunciation, contributes more to the positive manifold than other cognitive abilities. This is somewhat problematic for approaches such as Process Overlap Theory, which attempt to reconcile the concepts of modularity with the positive manifold. Although the theory can potentially explain why many modular processes could exist and still show the matrix of inter-correlates, it cannot be well extended to lexical tasks such as word pronunciation.

Without convincing support for approaches such as Process Overlap Theory, the paradox of the *g* factor coexisting with cognitive modularity remains. However, we very tentatively suggest an explanation for why lexical ability dominates the positive manifold. The weakness of investment theory is that it implies a ‘blank slate’. However, it has been proposed that when children learn vocabulary, they already have a conceptual system that involves innate structure and processes, and that lexical entries are fitted into this conceptual system (Bloom, 2001; Jensen, 2001). The most extreme version of this was presented by Fodor (1975), and has been described as ‘radical concept nativism’. Although few people take such an extreme view, modern cognitive approaches tend to acknowledge both nativist and empiricist aspects of human language acquisition (Piantadosi & Jacobs, 2016).

Furthermore, vocabulary ability is highly heritable, in fact the most heritable of the tests used in intelligence batteries (Kan et al., 2013). It stands to reason that the actual lexical entries are learnt, not inherited. Therefore, the quality or efficiency of the underlying conceptual system appears to be the part under genetic transmission. In this sense, variation in lexical skill is somewhat heritable.

Process Overlap Theory can explain most of the phenomena of the positive manifold, by suggesting a set of cognitive control mechanisms. If aspects of a partially innate conceptual system are integrated into those domain-general mechanism, then the depth of an individual’s lexical ability would also feature heavily in the positive manifold, which is what is found. Although highly speculative, this is actually consistent with the formulation of a core part of domain-general processing, working memory. The most recent version of the Multi-component Working Memory Model (Baddeley, 2003) includes substantial interaction between ‘fluid systems’ (i.e., working memory components) and ‘crystalized systems’ (i.e., long-term memory, LTM). Furthermore, many memory researchers have proposed that all memory is essentially LTM, but that through a focus of attention, a small set of representations can be activated (e.g., Jonides et al., 2008). This further links conceptual-LTM systems to domain-general processing such as those commonly identified as working memory. Under such a scheme the on-line processing associated with ‘working memory' would be substantially integrated within conceptual-lexical stores.

Additionally, the overlap of higher-level control systems envisaged in Process Overlap Theory could feasibly include cognitive control mechanisms operating within the language system. These appear to drive top-down lexical item selection and are somewhat interweaved with the functioning of ostensibly domain-general working memory (Bourguignon & Gracco, 2019). This, admittedly speculative, approach is more or less consistent with Process Overlap Theory, and thus inherits that theory's ability explain both the positive manifold, and widespread cognitive modularity.

In summary, we argue that lexical knowledge may vary within the population partly due to factors other than those proposed by investment theory. Some variation in lexical ability is due to the interaction of exposure to culture and inherited conceptual-language potential. Furthermore, conceptual information and fluid processing are often involved in the same cognitive processes. Individuals with better conceptual systems will likely have better lexical knowledge, and better fluid cognitive performance. Consequently, lexical ability correlates highly with many other cognitive skills, without being a sort of epiphenomenon of fluid processing.

Some limitations of the current work should be recognized. Eight of the eleven tests that we employed were taken from a standard intelligence test (WAIS-IV), and so would be expected to inter-correlate. Thus, the demonstration of a positive manifold in the current research was quite predictable. Secondly, our observation that lexical tasks dominate the *g* loadings, is limited by the classification of lexical and non-lexical tasks, which is somewhat arbitrary. For example, Arithmetic could be said to be somewhat verbal, as could Digit Span, as both require manipulation of numbers. We can only argue that some of the tests, such as the WAT and SpanLex definitely require lexical processing, while some, such as Block Design and Coding, do not, on the surface, appear to. On the other hand, some vagueness in the classifications is actually consistent with our argument that the observed results are a consequence of conceptual knowledge systems and ostensibly fluid processing overlapping more than is generally recognized within differential psychology or cognitive science.

Our use of factor analysis could also be seen as a limitation, given that some of the theories we explored propose a modular or network structure. Arguably, network analysis would be more appropriate (Kan, van der Maas, & Levine, 2019). However, factor analysis and network analysis tend to produce the same information (Schmank et al., 2021).

Conclusions and Future Work

Here we replicated the positive manifold of cognitive test intercorrelations, which underlies *g*. This is not a novel finding, but still relevant, as it is a replication in a non-WEIRD content. We further show that lexical tasks are substantially *g* loaded. Again, this has previously been noted, however, the phenomenon is frequently ignored, and raising this issue again here is justified. Further, the strong relationship of lexical ability to the *g* factor still lacks comprehensive explanation. Here, we propose that this may be due to the often overlooked, and considerable, interaction between conceptual and lexical information in LTM (i.e., semantic memory) with active domain general processing. This latter factor, in combination with a largely modular cognitive system may be responsible for the phenomenon of the positive manifold. We are currently exploring in silico simulations of the interactions between domain-general working memory processes and lexical information, and we hope that this may shed further light on the issues raised by the positive manifold.

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