Visualization, Inductive Reasoning, and Memory Span as Components of Fluid Intelligence: Implications for Technology Education

Abstract

The philosophy and epistemology of technology education are relatively unique as the subject largely focusses on acquiring task specific relevant knowledge rather than having an explicit epistemological discipline boundary. Additionally, there is a paucity of intelligence research in technology education. To support research on learning in technology education, this paper describes two studies which aimed to identify cognitive factors which are components of fluid intelligence. The results identify that a synthesis of visualization, short-term memory span and inductive reasoning can account for approximately 30% to 40% of the variance in fluid intelligence. A theoretical rationale for the importance of these factors in technology education is provided with a discussion for their future consideration in cognitive interventions.

Key Words: Technology education, Learning, Fluid intelligence, Spatial ability, Cognitive interventions.

1. Introduction

Considering learning as "a change in long-term memory" (Kirschner, Sweller, & Clark, 2006, p.75) which "involves the acquisition of knowledge" (Mayer, 2002, p.226), it is important, within specific educational contexts, that appropriate pedagogical strategies are identified which can support knowledge acquisition. In adopting this view of learning it is also important that knowledge is considered broadly to describe multiple types of knowledge including, for example, declarative knowledge, procedural knowledge, strategic knowledge, and wisdom (Gorman, 2002). Furthermore, knowledge can be both tacit and explicit (Collins, 2010). In relation to learning, the Organisation for Economic Co-operation and Development (OECD) noted how, for more than a century, approximately one in six students reportedly dislike school, don't attain sufficient levels of literacy and numeracy to become securely employable, and have disrupted or withdrawn from lessons (OECD, 2002, 2007). From this they speculate that the traditional education system may be "brain-unfriendly" and may be offending one in six learners (OECD, 2007, p.156).

While the OECD's report predominantly focuses on an agenda to translate and apply neuroscientific evidence within education, it acknowledges the capacity of cognitive psychology to contribute to understanding learning processes. One area of cognitive psychology which is often contextualised in understanding learning is the area of individual differences. Individual differences in learners can describe cognitive, conative, physical or physiological differences (Manichander, 2016). Individual cognitive differences have long been acknowledged as critical within education (Cronbach, 1957; Paterson, 1957) and now typically describe differences in relation to cognitive factors (Carroll, 1993; Kvist & Gustafsson, 2008; Schneider & McGrew, 2012). This paper focusses predominantly on one such factor, fluid intelligence, and its relationship with other cognitive factors, with the aim of contributing empirical evidence to support technology education research and practices. Fluid intelligence can be defined as "the use of deliberate mental operations to solve novel problems (i.e., tasks that cannot be performed as a function of simple memorization or routine)" (Primi, Ferrão, & Almeida, 2010, p.446). These include drawing inferences, concept formation, classification, generating and testing hypotheses, identifying relations, comprehending implications, problem solving, extrapolating, and transforming information (Kane, 2005; McGrew, 2009; Primi et al., 2010). Along with crystallised intelligence, defined as "accessible stores of knowledge and the ability to acquire further knowledge via familiar learning strategies" (Wasserman & Tulsky, 2005, p.18), it is one of the two general factors of intelligence posited in the Gf-Gc theory (Cattell, 1941, 1943).

Technology education is a relatively unique discipline due to its epistemological fluidity (Norman, 2013). Contemporary technology education is acknowledged to have the potential to develop and deliver outcomes of autonomy, creativity, problem solving, self-actualization, critical reflection/appraisal and communication skills (Barlex, 2007; Kimbell, 2000; Williams, 2009). A characteristic of technology education which is considered integral to the achievement of these outcomes is its emphasis on applied problem solving whereby the knowledge needed to solve a problem may not be necessary to solving future problems. As such, compared to many other subject areas such as mathematics, science and engineering, there is less of an emphasis on the acquisition of large quantities explicit content knowledge. Instead, "the domain of knowledge as a separate entity [in technology education] is irrelevant; the relevance of knowledge is determined by its application to the technological issue at hand" (Williams, 2009, pp.248-249). Knowledge is still valued in technology education but it is less transferable between problems than it is in many other subjects. In line with this, fluid intelligence has been identified as a causal factor in general learning as it supports the acquisition of knowledge and skills

(Kvist & Gustafsson, 2008; Primi et al., 2010). Therefore, this paper focuses on fluid intelligence rather than crystallised intelligence as it aligns more closely with the philosophy and epistemology of technology education.

2. Theoretical framework

Prior to describing fluid intelligence and its potential relationship with technology education in more detail, a brief overview of cognitive factors is required. Within the pertinent literature there is much debate regarding the definition of intelligence and there are many different approaches taken to studying it. One way that intelligence has been conceptualised is as a group of discrete cognitive abilities or factors including for example, spatial ability, verbal ability and reasoning ability (Carroll, 1993; Guilford, 1967; Horn & Cattell, 1966; Johnson & Bouchard Jr., 2005; Schneider & McGrew, 2012). It has also been considered in terms of mental processes such as planning, attention, and negotiating information in sequential or holistic approaches, rather than on discrete cognitive abilities (e.g. Das, Naglieri, & Kirby, 1994; Kaufman & Kaufman, 1983; Luria, 1980). Within the cognitive factor perspective there is disagreement relating specifically to the existence of factors and relationships between factors. For example, certain theories describe intelligence in terms of a hierarchical model (Carroll, 1993; Johnson & Bouchard Jr., 2005; Schneider & McGrew, 2012) whereas other describe intelligence as a bifactor model (Gignac, 2016; Maccann, Joseph, Newman, & Roberts, 2014). The theoretical framework subscribed to in this study is the Cattell-Horn-Carroll (CHC) theory (McGrew, 2005, 2009; Schneider & McGrew, 2012). It was primarily selected as it contains the fluid intelligence factor which is posited to be a critical factor in technology education. Furthermore, is has strong empirical support and a comprehensive compilation of additional factors adding to its utility for education research. An illustration of the structure of this framework is presented in Figure 1. It is a hierarchical factor model containing three strata. At the top level it contains one third-order factor which describes Spearman's (1904) conception of a general intelligence, *g*. It then contains 16 second-order factors similar in nature to what Thurstone (1938) described as primary mental abilities or group factors. Finally, associated with the second-order factors, it contains 84 specific first-order factors which describe specific mental abilities.

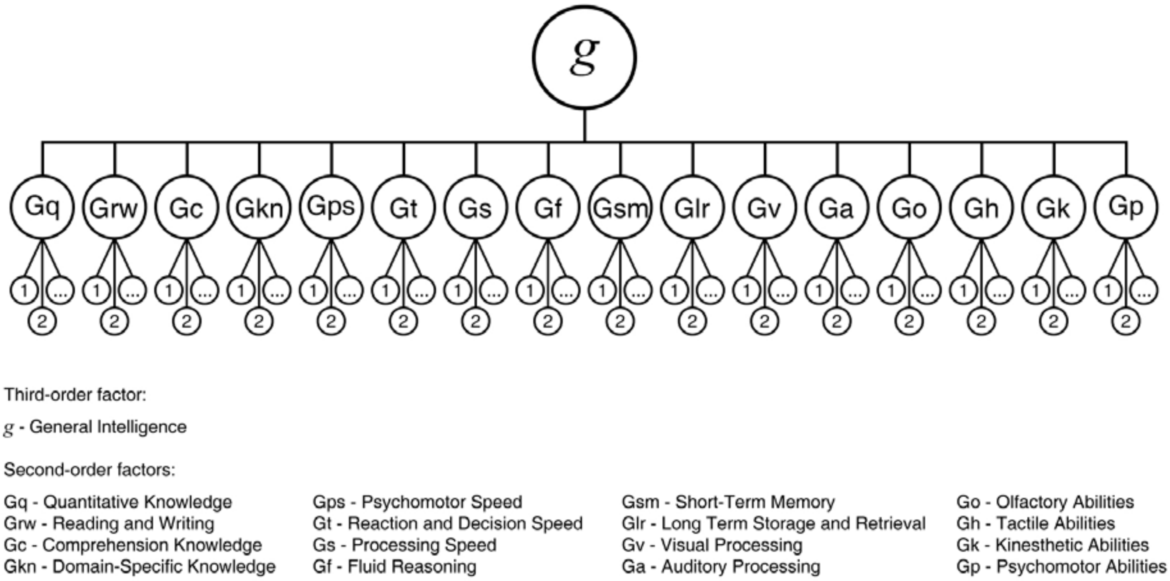

Figure 1. The structure of the Cattell-Horn-Carroll (CHC) theory of intelligence (Schneider & McGrew, 2012)*. Figure originally published by* Buckley, Seery and Canty (2018) *under a Creative Commons 4.0 International license (CC BY 4.0).*

The CHC theory was created through the synthesis of two other well-established theories, Carroll's (1993) three-stratum theory and the Gf-Gc theory. The three-stratum theory (Carroll, 1993) is the result of a meta-analysis of 461 datasets and was the first empirically based taxonomy that presented all established cognitive factors into a single organised framework (McGrew, 2009). The three-stratum theory was the larger contributor of factors to the CHC theory and many of these are examined in this paper. The main contributions from the Gf-Gc theory were the two second-order factors of fluid and crystallised intelligence. Cattell (1943) conceived his theory of fluid and crystallised intelligences from observations of intelligence tests designed for children and their lack of applicability to adult populations. Cattell (1943) postulated the potential for general intelligence to comprise of two separate entities by synthesising observations of adult dissociation of cognitive speed from power and the diminished *g* saturation in adult intellectual performances with neurological evidence. Specifically, this neurological evidence included the identification of a localised brain legion as effecting children generally while a corresponding legion effected adults more in terms of speeded tasks, abstract reasoning problems, and unfamiliar performances than in vocabulary, information and comprehension (e.g. Hebb, 1941, 1942).

While the CHC theory is one of the most contemporary and widely adopted frameworks describing cognitive factors, it is not unanimously accepted. Johnson and Bouchard Jr. (2005), in a large scale psychometric study, evaluated the statistical performance of the Gf-Gc theory, three-stratum theory and Vernon's (1950, 1964) verbal-perceptual model. They found that adjusting Vernon's (1950, 1964) model to include mental rotations as a second-order factor, creating what they propose as the VPR theory, that it was a better statistical fit for the data than both the Gf-Gc theory and the three-stratum theory. The VPR theory describes a hierarchical model containing three layers similar to the CHC theory but with only three second-order factors, verbal ability, perceptual ability, and rotation ability. Subsequently, Major, Johnson and Deary (2012) compared the VPR, Gf-Gc and CHC models using another large scale dataset and again determined that the VPR model had the best model fit for the data. These results suggest that the VPR model is the best statistical model to describe the structure of human intelligence and Johnson and Bouchard Jr. (2005) provide a theoretical discussion describing why it is better than the Gf-Gc theory. However, there is still debate regarding which of these theories is most appropriate. Schneider and Newman (2015) describe the peculiarity of considering mental rotations at the same conceptual level as verbal and perceptual abilities as it has long been acknowledged as a first-order factor of spatial ability in that it describes a specific mental process. Furthermore, Choi et al. (2008) present neuroscientific evidence which they describe as supporting the Gf-Gc theory. Finally, Waschl (2017) describes some factor analytic methodological implications for interpreting the factors in both the VPR and Gf-Gc models. A conclusive decision of the best model to describe human intelligence is beyond the remit of this paper. Other than subscribing to the CHC theory due to its posited utility for technology education as it contains the factor of fluid intelligence, this paper does not serve to contest the validity of other models such as the VPR model.

3. Fluid intelligence and technology education

There is a paucity of intelligence research conducted in technology education. Considering the relationship between intelligence and characteristics such as creativity, leadership, educational outcomes and mental health (Ritchie, 2015), it is paramount that it is considered more in discipline. There is a need to address the gender imbalance in technology education (e.g. DES, 2007) and there is much related research concerning attitudes towards both technology and technology education (Ardies, de Maeyer, & Gijbels, 2013; Ardies, De Maeyer, Gijbels, & van Keulen, 2014). Intelligence research, beginning with the postulated relationship between fluid intelligence and technology education, could support these agendas. Currently, there is no direct evidence which suggests fluid intelligence is important to the discipline. However, based on the characteristics of technology education and evidence from other related areas such as mathematics, engineering and science, it is possible to hypothesise that fluid intelligence would be a contextually fundamental factor.

Considering the aforementioned definition of learning as involving the acquisition of knowledge, technological knowledge is largely considered to describe the application of scientific knowledge (de Vries, 2016). McCormick (1997) suggests that explicit technological knowledge will be relative to specific tasks and circumstances and Kimbell (2011) argues that technological knowledge is inherently different to scientific knowledge whereby scientific knowledge is concerned with literal truths with technological knowledge being more aptly associated with usefulness. Furthermore, Kimbell (2011) suggests that provisional knowledge is more aligned with the discipline and that learners reside in an "indeterminate zone of activity where hunch, half-knowledge and intuition are essential ingredients" (p.7) in using their provisional knowledge to support further inquiry in response to particular tasks and problems. Recognising the centrality of applied problem solving in technology education and the agenda within technology education to facilitate students in ascertaining the knowledge required to solve novel and applied problems, fluid intelligence appears as an auspicious cognitive faculty within the discipline. While it is yet to be directly determined if fluid intelligence has an effect on technology education performance, there is indirect evidence suggesting it is fundamental to the discipline. Buckley et al. (2018) found that traits similar to fluid intelligence, such as problem solving and abstract reasoning, were considered important in terms of STEM intelligence from the perspective of technology education students. In their study no factor similar to crystallised intelligence was found to be of perceived importance, a result which aligns with the nature of technology education. Fluid intelligence has been identified as a predictor of educational achievement in the related disciplines of mathematics (Primi et al., 2010; Xin & Zhang, 2009) and science (Yuan, Steedle, Shavelson, Alonzo, & Oppezzo, 2006). Furthermore, correlations between fluid intelligence and divergent thinking, an index of creativity (Batey, Chamorro-Premuzic, & Furnham, 2009; Batey, Furnham, & Safiullina, 2010; Furnham, Batey, Anand, & Manfield, 2008; Nusbaum & Silvia, 2011; Silvia, 2008), indicate the potential significance of fluid intelligence within technology education as it is considered to be a creative discipline (Atkinson, 2000; Chang, 2013; Cropley & Cropley, 2010).

The lack of intelligence research in technology education and the broadness in the definition of fluid intelligence creates the need for a model which describes fluid intelligence more specifically to give it more utility in the applied context of technology education. Fluid intelligence is a second-order factor and is recognized to comprise of explicit first-order factors (Ebisch et al., 2012). Considering its influence on novel problem solving, identifying the factors which are related to fluid intelligence would provide an empirically derived model to examine in the context of technology education achievement. Many cognitive factors have already been shown to correlate with fluid intelligence such as spatial ability (Colom, Contreras, Botella, & Santacreu, 2001), short-term memory (Bachelder & Denny, 1977a, 1977b; Conway, Cowan, Bunting, Therriault, & Minkoff, 2002), working memory (Engle, Tuholski, Laughlin, & Conway, 1999; Unsworth & Engle, 2005) and processing speed (Fry & Hale, 2000). With respect to spatial ability, more specificity is required when describing its relationship with fluid intelligence as multiple first-order factors exist within the faculty (Buckley, Seery, et al., 2018). Typically, it is spatial factors associated with cognitive power which demonstrate this relationship such as the visualization factor (Snow, Kyllonen, & Marshalek, 1984). With respect to processing speed, it would also be of interest to determine its role in fluid intelligence and if it has educational implications. It is posited, from an educational perspective, that processing speed would not be of significant importance as the impact of the variance in processing speed between learners would likely be negligible in most educational scenarios as it could easily be accommodated within pedagogical approaches. Finally, with respect to the relationship between fluid intelligence and memory it is also critical to understand the roles of both working memory and short-term memory. Engle, Tuholski, Laughlin and Conway (1999) provide a nuanced description of the difference between these constructs by proposing that the common variance reflects storage and the residual working memory variance reflects executive attention. Subsequently, Colom, Abad, Rebollo and Shih (2005) examined the relationship each had with general intelligence and concluded that "[working memory] and *g* are (almost) isomorphic constructs, although that isomorphism vanishes when the storage component of [working memory] is partialed out. This suggests that the short-term storage component of the [working memory] system is a crucial underpinning of *g*. Finally, [working memory] components unrelated to short-term storage predict *g* to a significant degree, although the specific nature of these non-storage components is still unknown" (p.632). While this study examined the relationships between working memory, short-term memory and general intelligence, the distinction between these two memory systems and the importance of both the storage and executive control processes can be considered critical to fluid intelligence as it is the closest second-order factor to *g* (Carroll, 1993; Ebisch et al., 2012). Importantly, Ebisch et al. (2012) note that while the narrow factors of induction, visualization, spatial relationships and quantitative reasoning have high loadings on fluid intelligence, they also have unique variance. Through an fMRI study examining these factors as potential components of fluid intelligence, Ebisch et al. (2012) present findings which support a common neural circuit as underlying general cognitive abilities shared by central cognitive tasks, however they also show task specific activation patterns which they posit may be responsible for specific variance in task performance. All of this foundational research has significantly evolved contemporary understandings of human intelligence. It is now critical from a pedagogical perspective to progress this work by exploring the potential importance of additional related factors, and identifying how each of these factors affects student learning and performance.

4. Research question and approach

As fluid intelligence has been shown to support the acquisition of knowledge, it is envisioned that identifying first-order factors which load on fluid intelligence will provide a model identifying specific factors associated with knowledge acquisition and learning. With this, it may be possible to aid the development of pedagogical strategies which can support technology students, both in terms of cognitive development interventions and specific pedagogical strategies. Reflecting on the hypothesis presented by the OECD (2002, 2007) that traditional education systems may be brain-unfriendly, developing such cognitive skills amongst students may support their capacity to engage with the subject. Therefore, the research question underpinning this study is to examine which first-order cognitive factors are statistically associated with fluid intelligence. Answering this research question aspires to provide a model for further exploring cognition and individual differences in technology education. Specifically, a selection of domain-free general factors and factors within the domain of visual processing (spatial ability) from the Cattell-Horn-Carroll (CHC) theory were examined which aligned with the functional and conceptual factors groupings within the theory (Schneider & McGrew, 2012). Further understanding the relationship between cognitive factors and technology education would facilitate the refinement and development of pedagogical approaches based on empirical evidence.

Two studies were conducted which involved the administration of well-established psychometric tests to two separate cohorts of undergraduate students with a similar demographic within STEM education. The first study involved the administration of 17 psychometric tests, one of which was the Ravens Advanced Progressive Matrices (RAPM) (Raven, Raven, & Court, 1998) which is an established indicator of fluid intelligence (Birney, Beckmann, Beckmann, & Double, 2017; Kyttälä & Lehto, 2008), with the remaining 16 being indicators of domain-free general factors and spatial factors from the CHC theory. Based on the results of the first study, factors with a statistically significant loading on fluid intelligence were incorporated into a second study. This second study served to confirm the results of Study 1. In Study 2, the variables of time taken to complete test items and mental effort exerted in these items were also considered.

The RAPM used in these studies is frequently used as a measure of fluid intelligence (e.g. Bates & Shieles, 2003; McCrory & Cooper, 2005; Thoma et al., 2005; Van Der Meer et al., 2010). Carpenter, Just and Shell (1990) argue that the RAPM assesses analytical intelligence which equates to the concept of fluid intelligence (Van Der Meer et al., 2010). Furthermore, a number of studies have shown that the RAPM has a high loading on a general intelligence factor (Alderton & Larson, 1990; Bors & Stokes, 1998). However, although they are closely linked, neuroscientific evidence differentiates general and fluid intelligence (Choi et al., 2008). There is further debate as to whether the RAPM also partially measures spatial ability. Schweizer, Goldhammer, Rauch and Moosbrugger (2007) found that the RAPM could be considered as a marker of fluid intelligence and figural reasoning, and that a broad spatial ability factor correlated with but did not predict performance beyond a reasoning factor. In contrast, Waschl, Nettelbeck and Burns (2017) found that spatial ability contributed to performance in the RAPM over and above fluid ability highlighting the contention that still exists in relation to this instrument. Therefore, while the paper describes relationships between cognitive factors, it is important to acknowledge that these cognitive factors can only be interpreted relative to the tests used as indicators of them.

5. Study 1

5.1. Method

5.1.1. Participants

A cohort of 3rd year undergraduate students (n = 85) enrolled in an Initial Technology Teacher Education (ITTE) programme participated in this study. The students' primary fields of study were technology education and engineering education, wherein they studied discipline specific content, foundational educational studies, and subject specific pedagogy. The cohort consisted of 80 males and five females. Their ages ranged from 19 to 31 with a mean of 21.19 and a standard deviation of 2.41. Participation in this study was voluntary.

5.1.2. Psychometric tests

Participants were invited to take a total of 17 psychometric tests, 16 of which represented a unique first-order factor of human intelligence (Schneider & McGrew, 2012) and one test, the RAPM, served as a measure of fluid intelligence. Tests were predominantly adopted from the Educational Testing Services' (ETS) Kit of Factor-Referenced Cognitive Tests (Ekstrom, French, Harman, & Derman, 1976a), however additional tests were utilised to reflect advances in psychometric research. The second-order factors included in this study were visual processing (spatial ability), long-term memory, short-term memory, general reasoning, and processing speed. Tests were selected to provide a broad representation of domain-free general capacities and the visual processing faculty from the CHC. Table 1 provides a detailed description of each test utilised within this study.

Participants engaged with the tests in five groups of approximately 17 people. The tests were administered over a course of four test sessions with one week passing between each session. No session lasted longer than 60 minutes in duration and tests were administered in a different order to each group to remove the potential for an order bias within the data.

Table 1. Psychometric tests utilised in Study 1

Test *(second-order factor: first-order factor)*
RAPM *(fluid intelligence)*
For each problem, participants were presented with a 3 x 3 matrix containing eight abstract figures and one empty space. Participants had to select one of nine multiple choice answers which would fit the pattern of the matrix. The test contains two parts and both were administered to participants. The first part served to introduce participants to the test

Test *(second-order factor: first-order factor)*
format. The 32 items from part two of the test were considered in the data analysis. A total time of 40 minutes was afforded for the second part of the test.
ETS Paper Folding Test *(visual processing: visualization)*
For each problem, participants were presented with a series of illustrations showing a piece of paper being folded up to three times and having a hole punched in it. Participants had to select one of five multiple choice answers which would identify the piece of paper after it had subsequently been unfolded. The 20 items across parts one and two of the test were used. A total time of three minutes was afforded for each part of the test.
Mental Rotations Test *(visual processing: spatial relations)*
For each problem, participants were presented with an abstract stimulus constructed of an arrangement of cubes. Participants had to select two of four multiple choice answers which identified the original stimulus but in a different orientation with the remaining two being different (mirror images). The 24 items across parts one and two of the test were used. A total time of three minutes was afforded for each part of the test.
ETS Card Rotations Test *(visual processing: speeded rotations)*
For each problem, participants were presented with an abstract 2-dimensional stimulus. Participants had to identify if eight successive stimuli were the same or different (mirror images) to the original stimulus. The 160 items across parts one and two of the test were used. A total time of three minutes was afforded for each part of the test.
Perspective Taking Spatial Orientation Test *(visual processing: spatial orientation)*
For each problem, participants were presented with an array of images that represented real life objects (e.g. a tree, car and house), and instructions telling them which object they were to imagine being their location, which object they had to imagine they were facing, and which object they had to mentally point to. Participants had to identify which direction they were pointing in on a chart immediately below the array of objects. The 12 items from the test were used. A total time of five minutes was afforded for the test.
ETS Gestalt Completion Test *(visual processing: closure speed)*
For each problem, participants were presented with an incomplete image of a real life object (e.g. a flag or hammer). Participants had to identify what the object in each image was. The 20 items across parts one and two of the test were used. A total time of two minutes was afforded for each part of the test.
ETS Hidden Patterns Test *(visual processing: flexibility of closure)*
For each problem, participants were presented with a 2-dimensional array of lines. Participants had to identify if a common line diagram was or was not present within the array. The 400 items across parts one and two of the test were

Test *(second-order factor: first-order factor)*
used. A total time of three minutes was afforded for each part of the test.
ETS Shape Memory Test *(visual processing: visual memory)*
For each problem, participants were presented with an array of abstract visual stimuli which they had to memorise. Participants had to identify if a selection of abstract stimuli were or were not present within the memorised array. The 32 items across parts one and two of the test were used. A total time of eight minutes (four memorising, four answering) was afforded for each part of the test.
ETS Maze Tracing Speed Test *(visual processing: spatial scanning)*
For each problem, participants were presented with a 2-dimensional maze consisting of 24 adjoining sections. Participants had to identify the correct path through the maze. The 48 items across parts one and two of the test were used. A total time of three minutes was afforded for each part of the test.
Transformation Test *(visual processing: imagery quality)*
For each problem, participants were presented with verbal information describing instructions of how to mentally manipulate simple figures (e.g. letters, numbers and shapes). Participants had to identify the final figure after all instructions and illustrate this through a sketch. The 12 items across parts one and two of the test were used. A total time of 12 minutes was afforded for the test.
ETS Picture Number Test *(long-term memory: associative memory)*
For each problem, participants were presented with an array of images of real life objects and a number associated with each of them which they had to memorise. Participants had to identify the number associated with each object after the numbers were removed and the order of the images changed. The 32 items across parts one and two of the test were used. A total time of eight minutes (four memorising, four answering) was afforded for each part of the test.
ETS Toothpicks Test *(long-term memory: figural flexibility)*
For each problem, participants were presented with an image showing a pattern constructed of straight lines representing toothpicks and instructions describing a final pattern and how many lines must be removed. Participants had to identify a final pattern which conformed to the given rules in up to five unique ways. The 50 items across parts one and two of the test were used. A total time of six minutes was afforded for each part of the test.
ETS Auditory Number Span Test *(short-term memory: memory span)*
For each problem, participants were presented verbally with sequences of between four and 12 numbers with one second between each number in the sequence. Participants had to identify the exact sequences once all numbers in them had been announced. The 24 items in the test were used. A total time of eight minutes was afforded for the test.

Test *(second-order factor: first-order factor)*
ETS Figure Classification Test *(general reasoning: inductive reasoning)*
For each problem, participants were presented with either two or three groups of abstract visual figures where each group had a specific rule or condition regarding the figures within it which differentiated it from the other group(s). Participants had to identify which of the groups a series of additional figures belonged to. The 224 items across parts one and two of the test were used. A total time of eight minutes was afforded for each part of the test.
ETS Nonsense Syllogisms Test *(general reasoning: deductive reasoning)*
For each problem, participants were presented with a written statement, constructed with nonsensical content, which was exemplary of either good or poor reasoning. Participants had to identify if the statements illustrated good or poor reasoning. The 30 items across parts one and two of the test were used. A total time of four minutes was afforded for each part of the test.
ETS Finding A's Test *(processing speed: perceptual speed – letters)*
For each problem, participants were presented columns of 41 words, five of which contained the letter 'A'. Participants had to identify which of the words contained the letter 'A'. The 200 items across parts one and two of the test were used. A total time of three minutes was afforded for each part of the test.
ETS Identical Pictures Test *(processing speed: perceptual Speed – images)*
For each problem, participants were presented with an abstract 2-dimensional stimulus. Participants had to identify the identical stimulus within a set of five stimuli to its immediate right. The 96 items across parts one and two of the test were used. A total time of 1.5 minutes was afforded for each part of the test.

Note. All ETS tests came from the Kit of Factor-Referenced Cognitive Tests (Ekstrom et al., 1976a), additional tests included the RAPM (Raven et al., 1998), the Mental Rotations Test (Vandenberg & Kuse, 1978), the Perspective Taking Spatial Orientation Test (Hegarty & Waller, 2004), and the Transformation Test (Finke, Pinker, & Farah, 1989).

5.1.3. Data preparation and screening

Due to participants missing scheduled test sessions, 12.60% of the data (182 test scores) was missing from the complete dataset. In addition, eight participants did not finish the Perspective Taking Spatial Orientation Test within the allocated time limit and due to the approach taken in scoring this test this imposed a significant impact on the normality of the results. This was considered a valid reason to omit these scores from the dataset (Schneider & Roman, 2017). Combined, the missing scores corresponded to a total of 13.15% of missing data leaving a total of 1255 test scores in the dataset. The missing data was computed with a full-information maximum likelihood (FIML) estimate within the AMOS software (v.21, IBM SPSS Statistics). Based on recommendations for missing data when data is missing at random, this approach was selected to avoid the randomness introduced by imputation techniques and as it is relatively unbiased compared to traditional missing data techniques (Dai & Cromley, 2014; Davey & Savle, 2010; Dong & Peng, 2013).

As multiple linear regression analyses are sensitive to extreme outliers, the data was screened for both univariate and multivariate outliers prior to the conduction of these tests (Kline, 2016). Univariate outliers were identified as results which exceeded three standard deviations from the mean. Seven test results (0.48% of the dataset) were identified as univariate outliers under this criterion and were transformed to the value equal to three standard deviations from the mean (Kline, 2016). Data was then screened for multivariate outliers using both the Mahalanobis D and Cook's D statistics. The criterion for identifying outliers with the Mahalanobis D statistic was $p < 0.001$ (Kline, 2016) and for the Cook's D statistic was any instance greater than 1 (Cook, 1977). No data was identified as a multivariate outlier. The dataset which included the 1255 original test scores was used to determine the descriptive statistics (Table 2) and correlation matrix (Table 3) and the dataset with missing values computed and screened for outliers was used for the multiple linear regression analysis.

5.2. Results

Skewness and kurtosis values for all tests were within acceptable limits of between ±2 (Gravetter & Wallnau, 2014; Trochim & Donnelly, 2006). Despite some of the α values being below the recommended value of .7 (Nunnally, 1978), all of the tests utilised in the study are well-established and have been previously validated so this was deemed acceptable. Descriptive statistics for Study 1 are provided in Table 2.

Table 2. Descriptive statistics for Study 1

Task	N	M	SD	Range	Skewness	Kurtosis	α
1. Paper Folding	72	12.11	3.13	16.00	-.26	.13	.73
2. Mental Rotations	79	13.33	4.43	18.00	.13	-.85	.81
3. Card Rotations	65	114.29	24.33	95.00	-.04	-.66	.97
4. Perspective Taking	71	152.97	14.83	67.17	-1.04	.68	.63
5. Gestalt Completion	72	14.63	2.71	11.00	-.93	.45	.61
6. Hidden Patterns	72	217.65	55.75	286.00	-.49	.22	.98
7. Shape Memory	68	24.99	3.19	14.00	-.52	-.07	.56
8. Maze Tracing	82	30.35	6.58	33.00	.25	.42	.93

Task	N	M	SD	Range	Skewness	Kurtosis	α
9. Transformation	82	20.56	2.94	13.00	-1.21	1.38	.63
10. Picture Number	75	25.13	9.35	34.00	-.38	-.91	.91
11. Toothpicks	74	10.07	5.27	21.00	.28	-.74	.63
12. Auditory Number Span	82	10.01	2.75	14.00	.25	.02	.71
13. Figure Classifications	75	130.49	32.88	145.00	-.18	-.58	.98
14. Nonsense Syllogisms	73	14.53	4.16	20.00	.06	-.16	.80
15. Finding A's	63	50.94	12.67	59.00	.63	.39	.92
16. Identical Pictures	77	83.05	10.50	43.00	-.91	.31	.93
17. RAPM	73	23.43	4.97	25.00	-.61	.25	.87

A correlation analysis (Table 3) was conducted to provide an initial overview of factors which correlated with fluid intelligence as measured by the RAPM. Four factors showed moderate and statistically significant correlations including visual memory (Shape Memory Test) (r = .534, p < .01), visualization (Paper Folding Test) (r = .534, p < .01), inductive reasoning (Figure Classifications Test) (r = .453, p < .01), and associative memory (Picture Number Test) (r = .428, p < .01).

Table 3. Correlation matrix for Study 1

Task	Statistic	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. Paper Folding	Pearson's *r*	–															
	N																
2. Mental Rotations	Pearson's *r*	.439**	–														
	N	70															
3. Card Rotations	Pearson's *r*	.334*	.531**	–													
	N	58	62														
4. Perspective Taking	Pearson's *r*	.303*	.322**	.285*	–												
	N	62	71	55													
5. Gestalt Completion	Pearson's *r*	.282*	.325**	.262*	.280*	–											
	N	72	70	58	62												
6. Hidden Patterns	Pearson's *r*	.255*	.026	.032	.143	.239*	–										
	N	72	70	58	62	72											
7. Shape Memory	Pearson's *r*	.453**	.275*	.031	.360**	.289*	.241	–									
	N	62	64	57	56	62	62										
8. Maze Tracing	Pearson's *r*	.418**	.175	.359**	.068	.144	.209	.168	–								
	N	69	76	62	68	69	69	68									
9. Transformation	Pearson's *r*	.401**	.382**	.177	.145	.318**	.247*	.204	.272*	–							
	N	69	76	62	68	69	69	68	82								
10. Picture Number	Pearson's *r*	.145	.078	.160	.134	.167	.140	.426**	.201	.152	–						
	N	65	71	59	63	65	65	62	73	73							
11. Toothpicks	Pearson's *r*	.350**	.400**	.313*	.141	.122	.222	.072	.332**	.347**	.085	–					
	N	63	71	59	63	63	63	58	72	72	67						
12. Auditory Number Span	Pearson's *r*	.182	.287*	.224	.157	.168	.142	.186	.035	.037	.200	.119	–				
	N	69	76	62	68	69	69	68	82	82	73	72					
13. Figure Classifications	Pearson's *r*	.274*	.241*	.175	-.086	.139	.437**	.322*	.362**	.386**	.279*	.351**	-.046	–			
	N	65	71	59	63	65	65	62	73	73	75	67	73				
14. Nonsense Syllogisms	Pearson's *r*	-.034	.162	.114	.041	.102	-.030	-.017	.181	.182	.162	.065	.213	.027	–		
	N	63	70	58	62	63	63	57	71	71	66	73	71	66			
15. Finding A's	Pearson's *r*	.024	-.029	.100	.007	.298*	.090	.083	.066	.064	.115	-.119	-.014	.254	-.100	–	
	N	57	60	58	52	57	57	59	61	61	57	58	61	57	57		
16. Identical Pictures	Pearson's *r*	.300*	.277*	.466**	.009	.421**	.140	.148	.489**	.370**	.294*	.342**	-.102	.326**	-.122	.181	–
	N	70	74	62	66	70	70	65	74	74	69	68	74	69	67	61	
17. RAPM	Pearson's *r*	.533*	.218	.211	.181	.341**	.309*	.534**	.247*	.272*	.428**	.174	.122	.453**	.039	.126	.278*
	N	66	71	58	63	66	66	63	71	71	67	66	71	67	65	59	68

Note: **. Correlation is significant at the 0.01 level (two-tailed). *. Correlation is significant at the 0.05 level (two-tailed).

The final data analysis from Study 1 was the conduction of a stepwise multiple linear regression as an exploratory multivariate analysis to determine a potential model of factors with predictive power for fluid intelligence. The results (Table 4) indicate that the four factors with statistically significant and moderate correlations with fluid intellilgence formed a statistically significant model ($F(4,80) = 15.269$, $p < .001$), with a R^2 value of .433. Therefore, this model predicted 43.3% of the variance in fluid intelligence as described by performance on the RAPM.

Table 4. Stepwise multiple linear regression results from Study 1

IV	Model 1			Model 2			Model 3			Model 4		
	B	SE B	β	B	SE B	β	B	SE B	β	B	SE B	β
1	.451	.085	.504**	.406	.080	.455**	.369	.079	.413**	.306	.083	.343**
2				.200	.054	.329**	.167	.055	.275**	.130	.056	.214*
3							.200	.085	.216*	.178	.084	.192*
4										.299	.141	.209*
R^2	.254			.360			.401			.433		
ΔF	28.312**			13.559**			5.555*			4.473*		

Note: * $p < 0.5$. ** $p < 0.1$. Independent variables (IV): 1 = visualization (Paper Folding Test), 2 = associative memory (Picture Number Test), 3 = inductive reasoning (Figure Classification Test), 4 = visual memory (Shape Memory Test). Dependant Variable = fluid intelligence (RAPM).

6. Study 2

7.1. Method

7.1.1. Participants

A cohort of 4th year undergraduate students (n = 87) enrolled in the same ITTE programme as the 3rd year cohort from Study 1 participated in this study. The cohort consisted of 79 males and eight females. Their ages ranged from 21 to 33 with a mean of 22.63 and a standard deviation of 2.33. Participation in this study was voluntary.

7.1.2. Psychometric tests

Based on the results from Study 1, the five tests from the regression model (Table 4) were utilised with the Surface Development Test and the Letter Sets Test (Ekstrom et al., 1976a) so that the final battery of tests included two tests of visualization, two tests of memory span, and two tests of inductive reasoning to act as independent variables and the

RAPM remained as the dependent variable. Table 5 provides a detailed description of each test utilised in this study. Three of the tests, the RAPM, the Surface Development Test and the Figure Classification Test were adapted to include the Paas (1992) Cognitive Load Rating Scale after each item as a measure of mental effort. The Paas (1992) Cognitive Load Rating Scale is a nine-point self-report rating scale of invested mental effort. Each point contains a verbal description ranging from "very, very low mental effort" to "very, very high mental effort". Participants also recorded the start and end times for each item. Two minutes were added to each test to facilitate these amendments. Participants engaged with the tests in three groups of approximately 30 people. The tests were administered over a course of three test sessions with one week passing between each session. No session lasted longer than 60 minutes in duration and tests were administered in a different order to each group to remove the potential for an order bias within the data.

Table 5. Psychometric tests utilized in Study 2

Test *(second-order factor: first-order factor)*
RAPM* *(fluid intelligence)*
This test was also used in Study 1. See Table 1 for details.
ETS Paper Folding Test *(visual processing: visualization)*
This test was also used in Study 1. See Table 1 for details.
ETS Surface Developments Test* *(visual processing: visualization)*
For each problem, participants were presented with a pictorial image of a 3-dimensional abstract object and a representation of its surface development. Edges of the object in the pictorial image were denoted with letters. Edges of the surface development were denoted with numbers. Participants had to identify which lettered edge in the pictorial view corresponded with the numbered edges in the surface development. The 12 items across parts one and two of the test were used. A total time of seven minutes was afforded for each part of the test.
ETS Shape Memory Test *(visual processing: visual memory)*
This test was also used in Study 1. See Table 1 for details.
ETS Picture Number Test *(long-term memory: associative memory)*
This test was also used in Study 1. See Table 1 for details.
ETS Figure Classification Test* *(general reasoning: inductive reasoning)*
This test was also used in Study 1. See Table 1 for details.
ETS Letter Sets Test *(general reasoning: inductive reasoning)*
For each problem, participants were presented five sets of four letters. Four of the letter sets were derived from the

Test *(second-order factor: first-order factor)*
same rule (for example, consecutive letters) with one letter set not conforming to this rule. Participants had to identify the letter set which was different from the others based on it not conforming to the same rule. The 30 items across parts one and two of the test were used. A total time of seven minutes was afforded for each part of the test.

Note. * Tests were adapted to include the Paas (1992) Cognitive Load Rating Scale after each item as a measure of mental effort. Participants also recorded the start and end times for each item. Two minutes were added to each test to facilitate these amendments. All ETS tests came from the Kit of Factor-Referenced Cognitive Tests (Ekstrom et al., 1976a), the RAPM (Raven et al., 1998) was also administered.

7.1.3. Data preparation and screening

All participants engaged with each test however not all participants answered each item of each test. Raw scores were used to compute the descriptive statistics (Table 6) and correlation matrix describing correlations between performance scores (Table 7). To ensure results pertaining to time taken and mental effort invested weren't biased by missing data, items from the RAPM, the Surface Developments Test and the Figure Classifications Test were screened for low response rates (i.e. items not attempted during the test as opposed to items that participants were unable to answer). As participants were identifying the start and end times for each item, it was possible to identify items which were not attempted. One item from the Surface Developments Test and 11 items from the Figure Classifications Test had response rates of less than 85% and were therefore excluded from further analyses. Subsequent to this, there was 1.52% of missing data which was computed using a FIML estimate within the AMOS software (v.21, IBM SPSS Statistics). Finally, the data was screened for both univariate and multivariate outliers (Kline, 2016). Univariate outliers were identified as results which exceeded three standard deviations from the mean. Three data points (0.27% of the dataset) were identified as univariate outliers under this criterion and were transformed to the value equal to three standard deviations from the mean (Kline, 2016). Data was then screened for multivariate outliers using both the Mahalanobis D and Cook's D statistics. The criterion for identifying outliers with the Mahalanobis D statistic was $p < 0.001$ (Kline, 2016) and for the Cook's D statistic it was any instance greater than 1 (Cook, 1977). No data was identified as a multivariate outlier.

7.2. Results

Descriptive statistics for Study 2 are presented in Table 6. Skewness and kurtosis values for all tests were within acceptable limits of between ±2 (Gravetter & Wallnau, 2014; Trochim & Donnelly, 2006). Despite the α value of the Paper Folding Test and Shape Memory Test being below the recommended value of .7 (Nunnally, 1978), this was deemed acceptable as it has previously been validated.

Table 6. Descriptive statistics for Study 2

Task	n	M	SD	Range	Skewness	Kurtosis	α
1. RAPM	87	19.00	5.28	25.00	-.40	-.09	.80
2. Paper Folding	87	13.40	2.67	12.00	-.47	-.08	.65
3. Surface Developments Test	87	46.06	9.31	42.00	-.73	.05	.91
4. Shape Memory	87	24.38	3.72	17.00	-.05	-.46	.65
5. Picture Number	87	24.85	8.88	41.00	-.29	-.57	.90
6. Figure Classifications	87	126.35	27.49	127.00	.18	-.34	.96
7. Letter Sets Test	87	19.24	4.23	23.00	-.42	.49	.75

Two correlational analyses were conducted on the data from Study 2. The first (Table 7) examined correlations between raw performance scores. As all data was scale data the Pearson's *r* coefficient was used. All performance scores had statistically significant correlations with the RAPM except the Picture Number Test strengthening the reliability in the correlations found in Study 1.

Table 7. Correlation matrix of raw performance scores for Study 2

	1	2	3	4	5	6
1. Picture Number Test	-					
2. Shape Memory Test	.27*	-				
3. Letter Sets Test	.21*	.16	-			
4. Paper Folding Test	-.01	.14	.38**	-		
5. Surface Development Score	.10	.23*	.33**	.44**	-.	
6. RAPM	.22*	.37**	.38**	.39**	.40**	-
7. Figure Classifications Score	.15	.08	.22*	.36**	.37**	.29**

Note: Correlation coefficients describe Pearson's *r* values. **. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

The second correlation analysis was conducted using the dataset with items from the RAPM, the Surface Development Test and the Figure Classification Test which had low response rates (< 85%) removed and missing data was computed with the FIML estimate. As this analysis was conducted to examine correlations with perceived mental effort which is ordinal data, the Spearman's Rho (ρ) coefficient was used.

Table 8. Correlation matrix for Study 2 including time and effort variables

	1	2	3	4	5	6	7	8	9	10	11	12
1. Picture Number Test	-											
2. Shape Memory Test	.30**	-										
3. Letter Sets Test	.24*	.15	-									
4. Paper Folding Test	-.01	.12	.33**	-								
5. Surface Development Time	-.08	.01	-.29**	-.41**	-							
6. Surface Development Score	.10	.19	.32**	.36**	-.54**	-						
7. Surface Development Effort	-.11	-.18	-.22*	-.19	.44**	-.53**	-					
8. RAPM Time	.30**	.37**	-.01	-.12	.31**	.00	-.05	-				
9. RAPM Score	.20	.35**	.34**	.39**	-.23*	.41**	-.20	.42**	-			
10. RAPM Effort	.17	.05	-.09	-.22*	.08	-.09	.37**	.14	-.11	-		
11. Figure Classifications Time	-.09	-.04	-.12	-.19	.33**	-.14	.04	.35**	-.04	.28**	-	
12. Figure Classifications Score	.13	.20	.20	.40**	-.19	.40**	-.20	.23*	.54**	-.18	-.16	-
13. Figure Classifications Effort	-.12	-.24*	-.22*	-.19	.13	-.32**	.46[6]**	-.14	-.32**	.67**	.31**	-.46**

Note: Correlation coefficients describe Spearman's Rho (ρ) values. **. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

In relation to performance scores (Table 7), the RAPM test had a statistically significant correlation with all other tests. This result supports the reliability of the results obtained in Study 1 and suggests merit in the conduction of further analyses examining these factors as components of fluid intelligence.

In relation to time taken to complete test items, performance, and associated effort invested, a statistically significant correlation was observed between time taken and effort invested for the Surface Development Test items (ρ = .44, $p < .01$) and the Figure Classification Test (ρ = .31, $p < .01$). Additionally, statistically significant negative correlations were observed between performance and effort invested for the Surface Development Test items (ρ = -.53, $p < .01$) and the Figure Classification Test (ρ = -.46, $p < .01$). Statistically significant correlations were not found for these variables for the RAPM. These correlations indicate that having a higher ability level required less effort to be invested to solve test items for visualization and inductive reasoning tests.

Three multiple linear regression analyses were subsequently conducted to examine the predictive power of the visualization (Paper Folding Test), inductive reasoning (Figure Classification Test), visual memory (Shape Memory Test) and associative memory (Picture Number Test) factors on performance, time taken and effort exerted during the RAPM. A statistically significant regression equation was found between the four factors and performance ($F(4,82) = 14.226$, $p < .001$), with a R^2 value of .410. A statistically significant regression equation was also found between the four factors and time taken ($F(4,82) = 7.504$, $p < .001$), with a R^2 value of .268. Finally, a statistically significant regression equation was found between the four factors and effort exerted ($F(4,82) = 3.200$, $p = .017$), with a R^2 value of .135. These results indicate that 41% of the variance in performance in the RAPM can be attributed to visualization, inductive reasoning, visual memory, and associative memory. This is similar to the results of Study 1 which indicated that 43.3% of the variance in performance was explainable by these factors. Additionally, these factors were able to account for 26.8% of the variance in time taken to complete the test and 13.5% of the variance in perceived effort exerted. One final multiple linear regression analysis was conducted to examine the predictive power of the four factors on performance in the RAPM. However, in this analysis, performance in the Surface Development Test and Letter Sets Test were used instead of the Paper Folding Test and Figure Classifications Test to acknowledge the potential for the specific nature of tasks to influence the results. A statistically significant regression equation was found ($F(4,82) = 8.108$, $p < .001$), however this time an R^2 value of .283 was observed. In all regression analyses, each of the described independent variables contributed statistically significantly as predictors on the dependant variables (RAPM performance, time, and effort)

7. Discussion

The results of this study are relevant to technology education as they identify a selection of discrete cognitive factors which can be examined in practice, namely visualization, inductive reasoning and memory span. Through their relationship with fluid intelligence, it is hypothesised that they may be influential in student learning and performance within technology education. Considering the unique epistemology in technology education and the lack of intelligence research which has been conducted in the discipline to date, these results suggest a model which can support research exploring the link between intelligence and technology education achievement. Specifically, these results can be beneficial for technology education in two ways. Firstly, by providing a model which can be examined relative to performance both in terms of problem solving processes and overall achievement. Understanding the cognitive factors which are important within technology education would make the wealth of intelligence research associated with cognitive factors more tangible and accessible to the subject which would have large educational benefits. Secondly, there is evidence that visualization and inductive reasoning can be positively affected by targeted cognitive interventions and there is tentative evidence that working memory can be positively affected in a similar way. If these factors do indeed impact technology education performance, being able to enhance or train these abilities may offer an approach towards enhancing the technology students' capacity to learn.

Before discussing the implications of this research for practice in more detail, some limitations must be acknowledged. One limitation of the study includes the low number of tests adopted to represent each factor in Study 1. However, the agenda was exploratory and the results reflected those of similar studies in the field of human intelligence. Additionally, the results of Study 2 are similar to those from Study 1, giving confidence to the results illustrating the association between visualization, visual memory, associative memory and inductive reasoning with fluid intelligence. All regression models were statistically significant with 43.3% of the performance variance being explained in Study 1, 41% of the variance being explained in Study 2 when the same tests were considered from the regression model, and 28.3% of the variance being explained when different tests were used to represent the same factors. Furthermore, due to the contention described in the pertinent literature relative to what the RAPM measures, it is possible that describing the results as showing visualization, inductive reasoning and memory span as predictors of fluid intelligence may be inaccurate. It may be the case that these abilities are measured in the RAMP and these factors are better described as related to each other rather than predictive of each other. Making this distinction will only be possible when a categorical answer is provided for what the RAPM measures. This does not impact the utility of these results for technology education as identifying these factors as related to each other still allows for them to be examined relative to educational practices. As fluid intelligence is a second-order factor and visualization, inductive reasoning and memory span are first-order factors, the hierarchical nature of factors would describe them as components of fluid intelligence. Another limitation of this work relates to the gender imbalance in the study cohorts as female participation is underrepresented. While this is reflective of the gender distribution in technology education in many contexts, this has implications for the generalisability of the model to other disciplines as there are notable cognitive differences between males and females. Miller and Halpern (2014) note how females tend to perform better on verbal tasks with males typically performing better on spatial tasks. Considering most of the tests used in this study involved spatial stimuli, the results may be skewed by the gender distribution in the samples. Therefore, the continued development of this work merits investigation with more varied sample demographics to support its transferability and enhance its utility.

In translating these results into practice, it is important to consider the nature of each of these factors and the potential role they may have in both fluid intelligence and technology education achievement. The Picture Number Test measures associative memory which falls under the second-order factor of long-term memory. However, in the Kit of Factor-

Referenced Cognitive Tests (Ekstrom, French, Harman, & Derman, 1976b) it is described as a short-term memory process. This ambiguity is unfortunate and reflects the large degree of contention in verbal definitions for intelligence factors (Meehl, 2006). The test does involve making associations and also short-term memory storage. Making associations between information is an important learning process in terms of developing schema which exist in the long-term memory. However, it is difficult to separate the role of short-term memory within this process in terms of a psychometric test. Fluid intelligence has been shown to support the acquisition of knowledge (Kvist & Gustafsson, 2008; Primi et al., 2010) and its relationship with associational memory may contribute to this. However, the results of the two studies in this paper show statistically significant correlations between the Shape Memory Test and the Picture Number Test suggesting a common mechanism between visual short-term memory and associational memory which may be memory span. It is therefore difficult to identify exactly what is measured by this test, but due to the short amount of time (four minutes) that participants have to memorise the associations, it is posited for now to represent a memory span factor. Therefore, the three factors identified in this study as components of fluid intelligence are visualization, inductive reasoning, and what is arguably short-term memory span factor being described by the two memory tests. It is posited that the strength and significance in the association between memory span and fluid intelligence stems from the increased capacity to hold relative information in the working memory while problem solving. In terms of the association with visualization, it is posited that this supports the ability to generate and manipulate the information within the working memory. Finally, inductive reasoning is posited to provide people with the capacity to make inferences from the information stored in the working memory. By allowing for information to be retrieved, stored, generated, represented, manipulated and inferred, this model, both empirically and theoretically, can account for all of the necessary mental operations presented in established problem solving frameworks (Carlson & Bloom, 2005; Gigerenzer, 2001; Gigerenzer & Todd, 1999; Novick & Bassok, 2005; Schraw, Dunkle, & Bendixen, 1995; Wang & Chiew, 2010). As this model can account for the necessary processes, it is now important to examine exactly how they are employed in practice at discipline specific and task specific levels as it is posited that the significance of each factor will be situationally dependant.

Developing cognitive abilities should arguably become a fundamental aim of technology education. Expertise is often defined relative to acquired knowledge, however capability in technology education is argued to not necessitate large stores of knowledge in comparison to other subject areas as problems and tasks are often novel and contextually relative. Intelligence and pertinent knowledge have been shown to be complimentary in terms of problem solving and associated educational performance (Hambrick et al., 2012). However, while it can be difficult to define the necessary knowledge until a task is presented, as it the case with technology education, efforts invested in developing relevant intelligence factors can be universally beneficial. It is suggested that visualization, inductive reasoning and memory span can be posited as these relevant intelligence factors for technology education until they are examined more specifically relative to practice. In terms of training these abilities through targeted cognitive interventions, Sorby has developed an educational intervention to facilitate learners' spatial cognitive development (Sorby, 1999, 2009; Sorby & Baartmans, 1996). The results of this intervention have shown both that visualization can be developed, and that increasing students' levels of visualization can result in statistically significant STEM performance gains and improved retention (Sorby, 2009; Sorby, Casey, Veurink, & Dulaney, 2013). A meta-analysis conducted by Klauer and Phye (2008) has shown that inductive reasoning can also be developed and can result in better academic learning and positive transfer to problem-solving. Additionally, work has been conducted on working memory training where results tentatively present improvement at a construct level (Harrison et al., 2013). Finally, while there is currently contention surrounding the possibility of developing fluid intelligence through cognitive interventions (Au et al., 2015), the possibility to develop the constructs of visualization and inductive reasoning may both contribute to this debate and to students' capacity to engage and excel in technology education. In considering the impact that the intervention described by Sorby (2009) has had on STEM educational achievement and retention, developing complementary interventions to support inductive reasoning and working memory capacity may further increase the positive effects such training can have for students.

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