Investigating the effect of engineering student’s spatial ability and expertise on general complex problem solving

Clodagh Reid, Jeffrey Buckley and Rónán Dunbar

Spatial ability is attributed to success in STEM disciplines and is outlined as a component of general cognitive ability through the Cattell-Horn-Carroll (CHC) model of human intelligence. Research in spatially orientated disciplines outside of STEM has indicated that individuals with high levels of spatial ability and lower levels of expertise can perform to a similar standard as individuals with high levels of expertise when solving a discipline-specific problem. This indicates that spatial ability can support individuals in overcoming limitations in expertise. Through this research it is hypothesised that spatial ability will influence the performance of engineering students across different levels of expertise on a general complex problem-solving task.

Undergraduate students in their first (n=49) and third (n=48) years of study on civil, mechanical, and software engineering programmes were invited to participate. The Purdue Spatial Visualization Test and Rotations, Surface Development Test, and Paper Folding Test were used to obtain a measure of spatial ability for participants. The Tower of Hanoi, as an indicator of complex general problem solving, was administered and a 9-point Likert-type item was used as an indicator of the mental effort experienced by participants when they had completed the problem.

Through the analysis of the data no significance was found between performance on a complex problem-solving task and the expertise of the problem solver. This finding suggests that engagement in engineering education, at least that experienced by the participants, does not lead to the development of generic problem-solving skills. These findings are discussed in relation to the existing body of research and their contribution to further investigations into understanding the relationship between spatial ability and performance in solving engineering problems.

Keywords: Problem solving, Spatial ability, Expertise, Engineering education

Introduction

Engineering education focuses on supporting students in acquiring the necessary competencies to succeed in their future profession through engagement in applied educational frameworks (Crawley, Malmqvist, Östlund, Brodeur, & Edström, 2014; Savin-baden, 2014). These frameworks require students to develop and apply both domain-specific and domain-general competencies to advance their expertise. Domain-general skills are skills that, while they do not relate directly to a specific discipline, can be applied to a broad range of situations and settings and can be used to solve any problem in any area (Tricot & Sweller, 2014). It is contended that domain-general skills cannot be learned but can instead be applied to support the acquisition of discipline-specific knowledge (Tricot & Sweller, 2014). Domain-general skills and cognitive abilities can be used to support novices in the acquisition of domain-specific competencies as when a limited technical knowledge exists, individuals rely on other abilities to overcome this limitation (Hambrick & Meinz, 2011; Hambrick et al., 2016). Through this research the role of spatial ability, a cognitive ability related to success in STEM (Kell & Lubinski, 2013; Wai, Lubinski, & Benbow, 2009), and expertise are examined in relation to the performance of undergraduate engineering students on a general complex problem.

Background

Spatial ability in Engineering

The broad cognitive ability ‘visual processing’ is more commonly referred to as spatial ability in the literature (Buckley, et al., 2018). Visualization, a narrow cognitive factor at the core of spatial ability (Schneider & McGrew, 2012), is used as a proxy for spatial ability when examining the factor as it is the highest loading factor within its structure (Carroll, 1993). Within the empirical taxonomy of intelligence visualization is defined as “the ability to perceive complex patterns and mentally simulate how they might look when transformed (e.g., rotated, changed in size, partially obscured)” (Schneider & McGrew, 2012, p129).

The nature of the engineering profession and advancements in technology have contributed to the increasing complexity of engineering problems. Spatial ability is proposed to play an important role in problem solving and could contribute to supporting engineers and engineering students in solving complex problems (Hambrick et al., 2011; Ramey & Uttal, 2017). Disciplines of engineering, such as mechanical engineering, are perceived as highly spatially orientated, while it is also recognised that all disciplines of engineering are spatially demanding (Veurink & Sorby, 2012). Information is often communicated through visual means in engineering and engineering education e.g. CAD and engineering drawings (Chang, 2014; Chang et al., 2016; Olkun, 2003). Therefore, spatial abilities such as visualization may be necessary to understand the information presented to support the acquisition of expertise. Hambrick, et al. (2011), in the context of geology, determined that individuals with lower levels of expertise in an area and high levels of spatial ability can perform to a similar standard to those with high levels of expertise. However, to date, a study of this nature had not been carried out in engineering education until the current study.

Problem Solving

Problem solving describes when an individual is engaging with a task that they do not know how to go about solving using familiar procedures (Carlson & Bloom, 2005; Schoenfeld, 1983). When a problem is identified, problem solving can be considered as a search process in an individual’s memory to find a relationship between goals to reach a solution and a set of alternative paths (Carlson & Bloom, 2005; Mayer & Wittrock, 2006; Wang, 2007; Wang & Chiew, 2010). When problem solving, the domain of the problem will be either well-defined or ill-defined. The domain of the problem will greatly influence the type of problem, the problem-solving process and ultimately the solution that is reached (Jonassen & Hung, 2015; Jonassen et al., 2006). Well-defined problems may have constraints including that there is only one solution which can be determined with absolute certainty, and that there is a specific procedure which may be implemented to reach the solution to the problem (Dörner & Funke, 2017; Jaarsveld & Lachmann, 2017; Jonassen, 2000; Jonassen & Hung, 2015; Jonassen et al., 2006; Schraw et al., 1995). Ill-defined problems directly oppose this structure in that they are not well specified, may not be constrained, and the procedure to solve the problem may not be apparent or predictable (Dörner & Funke, 2017; Jaarsveld & Lachmann, 2017; Jonassen, 1997; Jonassen & Hung, 2015). Open-ended and undefined problems are frequently faced in technological disciplines in the form of design problems (de Vries, 2016; Gómez Puente et al., 2015). Therefore, problem structure is a critical to consideration when conducting research investigating engineering problem-solving performance.

Problem solving in Engineering Education

Contemporary third-level engineering education programmes implement a variety of frameworks to support the acquisition of engineering expertise (Crawley et al., 2014; Edström & Kolmos, 2012; Hanney & Savin-Baden, 2013; Savin-Baden, 2014). Problem solving is central to a number of these frameworks, whereby students engage in problems to develop their discipline expertise in situations similar to those experienced by practicing engineers (Edstrom & Kolmos, 2012). Advancement of expertise in an area has been attributed to deliberate practice and engagement in activities to improve performance in the area over a number of years (Keith & Ericsson, 2007). Although high levels of expertise do play a role in effective problem solving, when a student is negotiating a novel topic or task where they have limited technical knowledge, they rely on other abilities to overcome this deficiency (Hambrick & Meinz, 2011; Hambrick et al., 2016). Cognitive structures have been presented and discussed as possible predictors of problem-solving ability (Jonassen, 1997; Sweller, 1988), with Hambrick and Meinz (2011) also outlining that basic abilities contribute to novice performance and sometimes matter for expert performance. This research investigates the role of spatial ability and expertise in relation to the performance of undergraduate engineering students on a general complex problem.

Method

Undergraduate first (N = 63) and third (N = 52) year engineering students were invited to participate in this study. Ethical approval was sought and granted through the institutions Research Ethics Committee. Participant numbers were assigned to maintain participant anonymity. Participant details and records were stored securely in line with the institution's ethical guidelines for the handling and storage of data. Due to failures in recording equipment and misunderstanding of instructions n = 49 1st year and n = 48 3rd year engineering students were included in the data analysis for the study.

The study consisted of two sessions, in session one participants completed a complex problem and in session two spatial tests were administered to obtain a measurement of spatial ability. The Tower of Hanoi (TOH) was administered as it represents a complex problem-solving task (Eielts et al., 2018) through which complexity of the task can be increased through the addition of disks. In session one two problems were used, the 3- and 4-disk model. Participants were presented with the 3-disk TOH initially and the instructions for the task were explained. Participants were provided with the opportunity to ask questions to ensure that they understood the task. They were then instructed to begin the problem. Audio and video recording equipment was used throughout the problem-solving session to monitor performance. When the problem was completed participants were asked to indicate on a 9-point Likert-type item the amount of mental effort, difficulty, stress, and concentration they experienced when solving the problem. Following this, the 4-disk TOH was administered to participants with the same instructions provided as with the 3-disk TOH. A 9-point Likert-item was again administered to determine the mental effort, difficulty, stress, and concentration experienced.

In session two, participants were administered the Purdue spatial visualization test and rotations (PSVT:R) (Bodner & Guay, 1997), surface development test (SDT) and paper folding test (PFT) (Ekstrom, French, Harman, & Dermen, 1976). The order the tests were administered in was randomised to account for order bias.

Results

Preliminary data analysis has begun and it has been determined that there was not a significant difference between first year (M = 9.28, SD = 4.21) and third year (M = 9.93, SD = 3.42) engineering student's performance on the 3-disk TOH conditions; $t(73) = -0.69$, $p = 0.49$. There was also no significant difference found between the 1st year (M = 30.09, SD = 19.16) and 3rd year (M = 30.21, SD = 17.63) performance on the 4-disk TOH conditions; $t(73) = -0.03$, $p = 0.98$.

After establishing there were no significant differences in performance on the problem across levels of expertise, a correlation analysis was conducted between performance on the spatial tests and problem-solving performance. The results of this analysis are presented in Table 1. There were statistically significant correlations between each of the spatial test, as expected as each of the tests load on the spatial visualization factor (Bodner & Guay, 1997; Ekstrom et al., 1976). There was a low negative correlation (r= -.240) determined between performance on the PFT and moves made on the 4-disk TOH.

A further correlation analysis was conducted between spatial tests, performance, and self-reported responses for both tasks. The results of the analysis are presented in Table 2. This analysis highlighted a strong positive correlation (r=.815) between self-reported mental effort and difficulty on the 3-disk TOH. There were moderate positive correlations, ranging from (r=.550) to (r=.602), found between each of the other self-reported measures on the 3-disk TOH. There were low significant correlations between each of the self-report measures and the number of moves made on the 3-disk task. No correlations were determined between the spatial tests, performance, and self-reports on this task.

In relation to performance on the 4-disk TOH, strong positive correlations were found between each of the self-reported measures. Low correlations were found between the self-report measures for the 4-disk TOH and number of moves on both the 3- and 4-disk task. Significant correlations between self-reports on the 3- and 4-disk TOH tasks ranged from low (r=.394) to high (r=.762). There were low negative correlations identified between performance on the PFT and self-reported difficulty, stress and moves made on the 4-disk TOH.

Discussion

Through the preliminary data analysis, no significance between the expertise of the problem solver and performance on a complex problem-solving task has been found. Spatial ability has also not been found to significantly positively correlate to the performance of participants. Two potential reasons are put forward, whereby the institution involved does not place emphasis on training general complex problem solving, or that general complex problem solving cannot be developed. Tricot and Sweller (2014) argue that domain-general skills cannot be learned, however, individuals can apply these skills to new domains which supports the acquisition of discipline-specific knowledge rather than domain-general knowledge and skills. While it is outlined that domain-general problem solving cannot be learned, it is acknowledged that it can be used in educational settings to indicate to learners that an already acquired problem solving strategy can be applied to solve a domain-specific problem (Tricot & Sweller, 2014). The application of domain-general skills to support performance in a domain-specific task is supported by the circumvention-of-limits hypothesis whereby domain-general skills can be used to overcome a limitation in technical knowledge or when dealing with a novel task (Hambrick et al., 2016; Hambrick & Meinz, 2011).

As, to the best of our knowledge, no previous study has investigated the relationship between spatial ability and problem solving in the context of engineering with a comparative analysis across levels of expertise, this research contributes towards understanding this relationship. While spatial ability and expertise were found to have no impact on general complex problem-solving performance, future work aims to investigate the impact of spatial ability and expertise on authentic or domain-specific problem-solving performance in the context of engineering.

Table 1. Parametric correlations (Pearson)

		Year	PSVT Score	SDT Score	PFT Score	3-Disk Moves	4-Disk Moves
Year	*Pearson Correlation*						
	Sig. (2-tailed)	_					
	N						
PSVT Score	*Pearson Correlation*	-0.112					
	Sig. (2-tailed)	0.279	_				
	N	96					
SDT Score	*Pearson Correlation*	0.068	.590**				
	Sig. (2-tailed)	0.509	0.000	_			
	N	96	96				
PFT Score	*Pearson Correlation*	0.056	.478**	.599**			
	Sig. (2-tailed)	0.591	0.000	0.000	_		
	N	95	95	95			
3-Disk Moves	*Pearson Correlation*	0.081	-0.116	-0.064	-0.052		
	Sig. (2-tailed)	0.490	0.320	0.588	0.655	_	
	N	75	75	75	75		
4-Disk Moves	*Pearson Correlation*	0.003	0.022	-0.092	-.240*	0.215	
	Sig. (2-tailed)	0.977	0.853	0.432	0.038	0.064	_
	N	75	75	75	75	75	

Correlations

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 2. Nonparametric correlations (Spearman's Rho)

Correlations

			Year	*PSVT Score*	*SDT Score*	*PFT Score*	*3-Disk ME*	*3-Disk D*	*3-Disk S*	*3-Disk C*	*3-Disk Moves*	*4-Disk ME*	*4-Disk D*	*4-Disk S*	*4-Disk C*	*4-Disk Moves*
Spearman's rho	*Year*	*Correlation Coefficient*														
		Sig. (2-tailed)	–													
		N														
	PSVT Score	*Correlation Coefficient*	-0.104													
		Sig. (2-tailed)	0.312	–												
		N	96													
	SDT Score	*Correlation Coefficient*	0.061	.563**												
		Sig. (2-tailed)	0.558	0.000	–											
		N	96	96												
	PFT Score	*Correlation Coefficient*	0.076	.430**	.607**											
		Sig. (2-tailed)	0.464	0.000	0.000	–										
		N	95	95	95											
	3-Disk ME	*Correlation Coefficient*	-0.131	0.000	-0.009	-0.038										
		Sig. (2-tailed)	0.202	0.999	0.933	0.715	–									
		N	96	96	96	95										
	3-Disk D	*Correlation Coefficient*	-0.061	-0.023	-0.006	0.003	.815**	–								

Correlations

		Year	*PSVT Score*	*SDT Score*	*PFT Score*	*3-Disk ME*	*3-Disk D*	*3-Disk S*	*3-Disk C*	*3-Disk Moves*	*4-Disk ME*	*4-Disk D*	*4-Disk S*	*4-Disk C*	*4-Disk Moves*
	Sig. (2-tailed)	0.556	0.826	0.954	0.977	0.000									
	N	96	96	96	95	96									
3-Disk S	*Correlation Coefficient*	-0.023	-0.106	-0.126	-0.153	$.550^{**}$	$.557^{**}$								
	Sig. (2-tailed)	0.828	0.302	0.221	0.138	0.000	0.000	_							
	N	96	96	96	95	96	96								
3-Disk C	*Correlation Coefficient*	-0.021	0.016	-0.065	-0.012	$.602^{**}$	$.559^{**}$	$.585^{**}$							
	Sig. (2-tailed)	0.839	0.877	0.530	0.910	0.000	0.000	0.000	_						
	N	96	96	96	95	96	96	96							
3-Disk Moves	*Correlation Coefficient*	0.165	0.052	-0.010	-0.047	$.303^{**}$	$.252^{*}$	$.264^{*}$	$.398^{**}$						
	Sig. (2-tailed)	0.158	0.658	0.932	0.688	0.008	0.029	0.022	0.000	_					
	N	75	75	75	75	75	75	75	75						
4-Disk ME	*Correlation Coefficient*	-0.046	-0.065	-0.127	-0.169	$.639^{**}$	$.503^{**}$	$.453^{**}$	$.536^{**}$	0.165					
	Sig. (2-tailed)	0.657	0.530	0.216	0.101	0.000	0.000	0.000	0.000	0.157	_				
	N	96	96	96	95	96	96	96	96	75					
4-Disk D	*Correlation Coefficient*	-0.016	-0.071	-0.118	$-.228^{*}$	$.600^{**}$	$.560^{**}$	$.511^{**}$	$.513^{**}$	0.071	$.879^{**}$				
	Sig. (2-tailed)	0.879	0.492	0.251	0.026	0.000	0.000	0.000	0.000	0.543	0.000	_			
	N	96	96	96	95	96	96	96	96	75	96				

Correlations

		Year	*PSVT Score*	*SDT Score*	*PFT Score*	*3-Disk ME*	*3-Disk D*	*3-Disk S*	*3-Disk C*	*3-Disk Moves*	*4-Disk ME*	*4-Disk D*	*4-Disk S*	*4-Disk C*	*4-Disk Moves*
4-Disk S	*Correlation Coefficient*	0.035	-0.074	-0.142	-.218*	.460**	.394**	.600**	.407**	0.055	.724**	.779**			
	Sig. (2-tailed)	0.734	0.472	0.168	0.034	0.000	0.000	0.000	0.000	0.638	0.000	0.000	_		
	N	96	96	96	95	96	96	96	96	75	96	96			
4-Disk C	*Correlation Coefficient*	-0.026	0.017	-0.085	-0.129	.528**	.447**	.446**	.762**	.282*	.741**	.719**	.634**		
	Sig. (2-tailed)	0.801	0.870	0.412	0.214	0.000	0.000	0.000	0.000	0.014	0.000	0.000	0.000	_	
	N	96	96	96	95	96	96	96	96	75	96	96	96		
4-Disk Moves	*Correlation Coefficient*	0.037	0.004	-0.193	-.247*	0.152	0.125	0.044	0.093	.236*	.339**	.367**	.379**	.357**	
	Sig. (2-tailed)	0.753	0.974	0.098	0.033	0.193	0.285	0.707	0.427	0.042	0.003	0.001	0.001	0.002	_
	N	75	75	75	75	75	75	75	75	75	75	75	75	75	

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Conclusion

There are two main conclusions of this study:

1. Engagement in engineering education did not lead to the development of generic problem-solving skills for the sample included in this study.

2. Spatial ability did not have a significant correlation to the performance on a complex problem-solving task for the sample of individuals included in this study.

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