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A study of the relationship between learning styles and cognitive abilities in engineering students

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Learning preferences have been indirectly linked to student success in engineering programmes, without a significant body of research to connect learning preferences with cognitive abilities. A better understanding of the relationship between learning styles and cognitive abilities will allow educators to optimise the classroom experience for students. The goal of this study was to determine whether relationships exist between student learning styles, as determined by the Felder-Soloman Inventory of Learning Styles (FSILS), and their cognitive performance. Three tests were used to assess student's cognitive abilities: a matrix reasoning task, a Tower of London task, and a mental rotation task. Statistical *t*-tests and correlation coefficients were used to quantify the results. Results indicated that the global–sequential, active–referential, and visual–verbal FSILS learning styles scales are related to performance on cognitive tasks. Most of these relationships were found in response times, not accuracy. Differences in task performance between gender groups (male and female) were more notable than differences between learning styles groups.

Keywords: learning styles; cognitive performance; matrix reasoning; Tower of London; mental rotation

Introduction

Learning styles assessment

Learning styles assessments have been popular in engineering education since the 1990s, with instruments such as the Felder-Soloman Inventory of Learning Styles (FSILS) used to determine the preferred learning styles of both engineering and non-engineering students. The FSILS is a self-rated inventory, similar to personality-type tests. It consists of four scales that measure different learning styles preferences outlined by Felder and Silverman (1988):

(1) Active–reflective (ACT/REF): Active learners prefer to 'learn by doing', with hands-on activities, while reflective learners prefer internal and/or solitary reflection and analysis.
(2) Sensing–intuitive (SNS/INT): Sensing learners like dealing with facts and hard data, while intuitive learners like dealing with ideas.
(3) Sequential–global (SEQ/GLO): Sequential learners tend to learn in logical, linear stepwise fashion, while global learners tend to learn in nonlinear ways, making seemingly unconnected 'jumps' in knowledge.

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(4) Visual–verbal (VIS/VRB): Visual learners prefer to learn from visual or graphical information like graphs, charts, and pictures, while verbal learners prefer to learn from written or spoken words.

Engineering classes and methods of instruction are not always congruent with a student's preferred learning style, leading to discouragement and disengagement on the part of the student. A study by Graf, Viola, and Leo (2007) showed that while student performance in a course was not affected by matching course content presentation to their learning styles, the level of student effort and behaviour was definitely correlated with matching the course with learning styles. This supports the idea that students can become discouraged if classes are incongruent with their learning styles. This perspective has become increasingly important with the recent exploration of effective ways to present personalised learning content through distance and/or e-learning environments. Learning styles have been explored in the context of e-learning, with Poulova and Simonova (2012) reporting a relationship between use of different types of classroom materials and student learning styles as measured by the Learning Concepts Inventory.

Learning styles inventory (LSI) assessments can be informative in determining the learning preferences of students, but few studies have correlated student learning styles with cognitive abilities. The literature is inconsistent, but indicates that the FSILS may be more strongly correlated with subject-specific performance as opposed to overall cognitive strengths and weaknesses. The FSILS was originally developed in the context of Chemical Engineering students, so a subject-specific correlation makes sense. As an example, Padgett, Yoder, and Forbes (2011) examined the relationship between student performance on the Signals and Systems Concept Inventory (SSCI) and learning styles as measured by the FSILS. They discovered a significant positive correlation between number of correct SSCI questions and intuitive learning style, a significant negative correlation between active learning style and correct questions, and no correlation between reflective learning and correct questions. A *t*-test performed on their data indicated a significantly higher SSCI score for global learners compared to sequential, and for intuitive learners compared to sensing learners, while no difference was found comparing visual to verbal learners. Self and Widmann (2009) showed a positive correlation between performance on the Dynamics Concept Inventory and reflective learners, but no correlation with any other scale on the FSILS. The correlation of learning styles to concept inventories appears to be somewhat discipline specific based on the limited number of studies published in the literature. On the other hand, Giovanelli (2003) attempted to correlate the FSILS with visual memory using a visual memory task. They found no correlation with FSILS on any scale; rather they postulated that the visual memory scores correlated with different 'visualisation styles'. The task used eye-tracking and images to determine visual memory performance, a task developed by the study authors and not itself widely validated. The same author attempted to determine longitudinal variations in FSILS among physics students, but only showed weak preferences over time for visual and active styles. Even that correlation, according to the author, was not as strong as one would expect. A number of additional papers exist that examine the validity and robustness of the FSILS, with no clear consensus (Felder and Spurlin 2005; Litzinger, Lee, and Wise 2005; Zywno 2003). The classic paper by Coffield et al. (2004) examines and compares 16 LSI models and casts doubt on the overall validity of learning styles assessments in general. A data-driven statistical approach by Viola, Graf, and Leo (2007) suggests that part of the reason for inconsistencies in the literature may results from the multidimensional nature of the learning styles scales – specifically for the FSILS. The authors conducted an analysis that found multivariate dependencies between learning styles scales using a principal component analysis-based approach that evaluated each individual question. In general, the published studies on FSILS generally attempt to correlate the learning styles with performance in a specific class or on a concept inventory, with retention or success/failure within a given technical major, or with performance on a cognitive (often multidimensional and/or unvalidated) task.

Our goal was to determine any possible correlations between learning styles as measured by the FSILS instrument and performance on selected cognitive tasks in order to understand how learning styles impact cognitive processes found in engineering education. This specific instrument was used due to the fact that it was originally designed for engineering students and has been widely cited in the literature – the original paper has been cited over 3300 times according to Google Scholar. Because the FSILS is a self-assessment-based inventory, we were interested in how the learning styles identified by the inventory were related to performance on standard cognitive tests. We used a series of tasks designed to determine cognitive abilities across several domains that are needed in various engineering problems, including visual-spatial processing, analytical reasoning, and planning. The results of student performance on the selected tasks were compared with the FSILS to determine whether any relationships exist between learning styles preferences and cognitive abilities. The research was driven by two key questions. First, are self-assessed learning styles in any way related to performance on cognitive tasks? Two examples might be: would students with a strong visual learning preference actually exhibit a higher level of visual-spatial skill as measured by certain tasks and would students who have a sequential learning style perform better on tasks requiring stepwise planning than those who have a global learning style? Second, how can the combination of cognitive tasks and FSILS assessment yield insight into current issues facing the engineering education community? For example, how can engineering teaching styles and curriculum be adapted in ways to appeal to different learning styles, and will this be effective in increasing student persistence and success?

Cognitive tasks – overview

Cognitive tasks have been used, often in conjunction with neuroimaging studies, as a way of providing insight into how the brain functions while performing said tasks within a given cognitive domain. In this research, we used three cognitive tasks: a Tower of London (TOL) task, a mental rotation (MR) task, and a matrix reasoning task. These tasks were selected because they require a number of different cognitive skills important in engineering, including visual-spatial processing, analytical reasoning, and planning (as described in the next section), and because they have been extensively used by and adapted for the neuroimaging community – important because the study results presented here were part of a larger study involving electroencephalography (EEG) and functional magnetic resonance imaging (fMRI).

Visual-spatial processing has long been seen as a useful, if not essential, skill to successful problem solving in engineering. The ability to visualise in three dimensions (3D) and to mentally translate from two dimensions (2D) to 3D is important in engineering applications like rapid prototyping in manufacturing, visualisation of 3D vector fields like electromagnetic antenna patterns and thermal flows, and visualisation of construction drawings and plans. Spatial processing abilities in adolescents have been shown to predict later creativity in science and technology (Kell et al. 2013). Analytical reasoning skills are used in the recognition of patterns and trends in visually presented data – skills found in applications such as data mining, trend forecasting, interpretation of schematic diagrams, and growth or decay patterns. Planning skills are fundamental skills used in effectively planning out multistep solutions to the kinds of problems seen in electric circuits, thermodynamics, and other engineering problems requiring carefully planned steps to a solution. By correlating task performance with FSILS scores, we can determine how different learning styles preferences are related to specific cognitive skills.

The study presented in this paper is part of a much larger fMRI and EEG study (Hames and Baker 2013), which placed some practical time and space limits on how the tasks were presented and how participants could respond. For example, in the fMRI environment, participants cannot manipulate actual objects. These specific tasks have also been widely used in and adapted for the neuroimaging environment and have reasonably well-documented brain activation patterns. This section provides a little background on previous research that has been conducted on the selected tasks. A detailed description of how each task was implemented in this project is given in the section Methods.

Tower of London

The TOL task was originally developed to test impairments on non-routine tasks versus routine tasks, e.g. impaired planning (Shallice 1982). Studies suggested that multiple sub-processes of planning are involved in the TOL (Rowe et al. 2001). Rowe et al. conducted a positron emission tomography study to separate mental components involved in planning. They did not find evidence of evaluation of a path towards a specific goal. Instead, they only found the process of generating, selecting, and remembering moves.

The TOL task has been used to compare planning between females and males. It has been determined that sexes use different strategies to solve the TOL task (Boghi et al. 2006; Dagher et al. 1999). Males rely on visuospatial abilities and females on executive processing.

Few studies have looked at the effect of learning styles on performance of the TOL task. Cheetham et al. (2012) looked at the effect of verbal versus visual processing preference on the TOL. They found that the TOL tasks relied primarily on visuospatial memory resources as opposed to verbal memory. They did not find any influence from the participants' visual–verbal preferences on the variance of the TOL task. The TOL task was selected for comparison across sensing–intuitive and global–sequential learning styles; how information is taken in and processed, particularly at the planning level, might be expected to be different in students who process information sequentially as opposed to globally.

Mental rotation

The MR task is designed to measure visual-spatial abilities and involves the visual-motor regions of the brain. Particularly when rotating 3D images displayed in the 2D plane, individuals can approach the task in different ways, ranging from purely visual to verbally mitigated pattern identification. For example, Shepard and Metzler (1971) received comments from their participants that they perceived the two-dimensional block objects in three-dimensional space, allowing them to rotate the objects around an axis. There are three stimuli commonly used in MR: the 3D block stimulus, alphanumeric figures, and abstract objects (Jordan et al. 2001). There are also many ways to apply the task and test MR capabilities (Peters and Battista 2008). Studies either compare rotated images to determine whether they are identical or mirror images (Barnes et al. 2000; Cohen et al. 1996; Ecker et al. 2006; Jordan et al. 2002; Kosslyn et al. 1998; Tagaris et al. 1998), use translation of objects (Barnes et al. 2000; Tagaris et al. 1998), or match rotated objects (Lamm et al. 2007; O'Boyle et al. 2005).

Lamm et al. (2007) suggested that solving MR tasks is dependent upon visuo-motor processes and evokes neural processing that may simulate actual object rotation. Two studies compared motor rotation to MR (Wexler, Kosslyn, and Berthoz 1998; Wohlschläger 2001). They both found strong correlations between MR and motor rotation in response times and angle of rotation. Both studies asked participants to plan hand movements while performing MR. They found that the planning of hand movements, and not their execution, interfered with MR, suggesting that the two activities shared a common process and MR is an imaged action. One reason for the selection of MR for this study was the motor rotation aspect of the task and how it might relate to learning styles; specifically, active learners might be expected to take a more motor-oriented approach to the rotation task, resulting in different levels of accuracy and different response times from reflective learners, who might not engage the motor rotation processes in the brain to the same extent as active learners. The MR task also engages visual-spatial processes important in many engineering problems.

Matrix reasoning

The matrix reasoning task tests analytical reasoning abilities. It consists of a three-by-three matrix with a missing bottom right entry that must be selected from multiple choices. There are several known methods of separating questions. Carpenter, Just, and Shell (1990) divided the test into five basic rules:

(1) Constant in a row: The same value occurs throughout a row, but changes down a column.
(2) Quantitative pairwise progression: A quantitative increment or decrement occurs between adjacent entries in an attribute such as size, position, or number.
(3) Figure addition/subtraction: A figure from one column is added to or subtracted from another figure to produce the third column.
(4) Distribution of three values: three values from a categorical attribute are distributed in a row.
(5) Distribution of two values: two values from a categorical attribute are distributed in a row; the third value is null.

Given these rules, the missing entry in each problem can be found. Another method of dividing the questions is by analytic and visual (Hunt 1974). DeShon, Chan, and Weissbein (1995) concluded that the questions could be separated into visual-spatial and verbal-analytical questions. DeShon, Chan, and Weissbein's (1995) division maps closely to Carpenter, Just, and Shell's (1990) five rules (Mackintosh and Bennett 2005). Using the rules set by Carpenter, Just, and Shell (1990), Mackintosh and Bennett (2005) found that males performed better on tasks requiring addition/subtraction – or distribution of two – rules. The matrix reasoning task was selected for this study because it involves verbal and visual-spatial analysis – we anticipated that verbal learners and visual learners might perform differently on both the overall test and the visual-spatial and verbal-analytical sub-scales of the test.

Methods

Participants

This study was approved by a Human Subjects Internal Review Board. A total of 51 engineering students from a university in the USA volunteered for the study, 18 female and 33 male. The mean age was 22.4 ± 3.1 years. Figure 1 shows the distribution of engineering major types and classification (grade) levels of the participants. The terms freshman, sophomore, junior, and senior refer to first-, second-, third-, and fourth-year students, respectively. While we did not include ethnicity as a component in the study, it is important to note that the participants were drawn from a student population that included international students.

The sample of students represents about 2% of the population of engineering students from their engineering college. The distribution of engineering types underrepresents petroleum and civil majors, while electrical engineers are overrepresented. The female engineering population is also overrepresented.

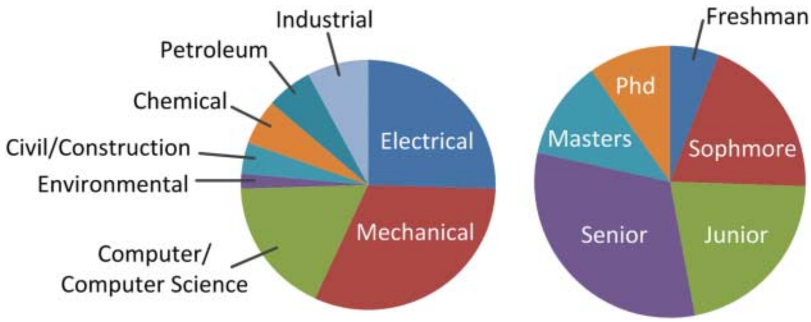

Figure 1. Distribution of engineering types (left) and grade levels (right).

Set-up

Study participants were asked to complete the FSILS and submit their scores to the investigators. They were then given three cognitive tasks using a computer-based testing system that presented the test questions and tracked scores and response times as participants responded using response pad buttons. Participants were asked to complete all three tasks within one session: a Tower of London task, a MR task, and a matrix reasoning task. The order of the tasks was random across participants to eliminate issues of fatigue or boredom that might impact the latter task results. All tasks were performed in a sound-proof, unlit room and were presented on a 10.25 by 13.25 monitor.

Task description

The TOL task was designed similarly to that described in Lazeron et al. (2000), with the images adopted by Shallice (1982). Participants were instructed to count the minimum number of moves required to arrange colourful balls on three pegs into a target position. Within the task there are two degrees of difficulty, easy and hard. The degree of difficulty is determined by the number of required moves to complete the task and by the number of discs. The hard sub-task always has four discs, while the easy sub-task has three. The hard sub-task requires four or five moves, while the easy sub-task requires two or three. There are a total of 42 stimuli for the TOL task. The stimuli are arranged in a block format with alternating blocks of three TOL and three baseline stimuli. The TOL blocks have both hard and easy sub-tasks to average out the effect of difficulty across blocks. Figure 2 shows examples of TOL sub-tasks.

The MR task was designed similar to that used by Shepard and Metzler (1971), involving '3D' figures. The participant is asked to match one of four figures with a top figure. The matching figure is either a rotated, mirrored, or identical version of the top figure. There are three kinds of rotations: rotation in the plane of the screen, depth of the screen, or a combination of both. There are a total of 48 stimuli for the MR task. The questions are arranged in a block format with

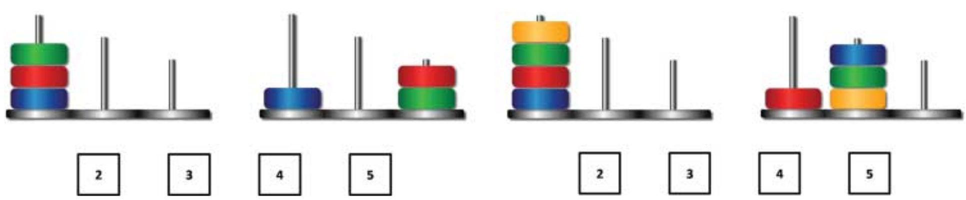

Figure 2. Examples of TOL tasks: easy (left) and hard (right).

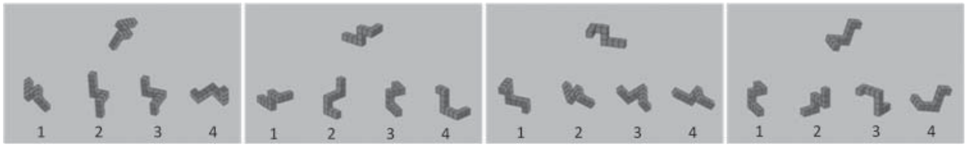

Figure 3. Examples of MR tasks (from left to right): plane rotation, depth rotation, combination rotation, and mirrored.

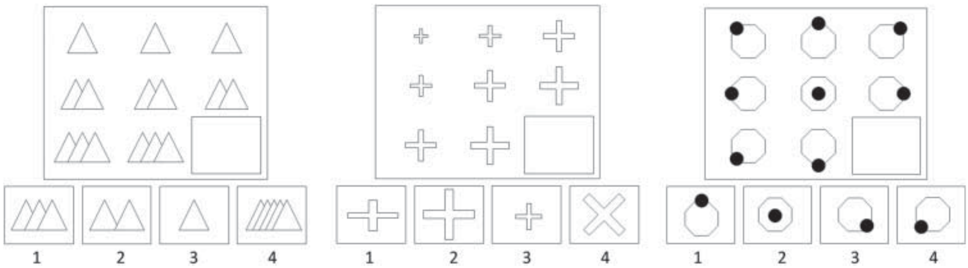

Figure 4. Examples of matrix reasoning tasks: verbal-analytical (left), ambiguous (centre), and visuospatial (right).

alternating blocks of three depth, three plane, three combination, three mirror, and four baseline stimuli. Figure 3 shows examples of MR sub-tasks (Hames and Baker 2013).

The matrix reasoning paradigm is set up according to the matrix reasoning paradigm used by Desco et al. (2011). Participants choose the bottom right missing shape that completes a nine-by-nine matrix. The matrix reasoning tasks can be separated into three types of sub-tasks: visuospatial, verbal-analytical, and ambiguous (A) (DeShon, Chan, and Weissbein 1995). Ambiguous is a combination of verbal-analytical and visuospatial. There are a total of 30 stimuli for the matrix reasoning task. The questions are arranged in a block format with alternating blocks: three visuospatial, three verbal-analytical, three baseline (no task) stimuli, and three ambiguous (only in the last block). Figure 4 shows examples of the matrix reasoning sub-tasks.

Results

Learning styles results

The FSILS assessment ranks participants in each of the four cognitive domains using a scale from 11a to 11b in increments of 2 (e.g. 11a/9a/7a, etc.). The distribution of learning styles for the students in this study is depicted in the histograms shown in Figure 5. For example, in the category of VIS/VRB, 9a–11a is a strong preference towards visual, and 9b–11b is a strong preference towards verbal. Scores between 1a/b–3a/b indicate a fairly well-balanced learning preference, and between 5a/b–7a/b indicate a moderate learning preference (Felder and Silverman 1988). Figure 5 shows the distribution of FSILS scores among the 51 engineering students for all four scales (Hames and Baker 2013).

When evaluating our data and results, we used two different approaches. The first approach was to compare one learning style with another for each FSILS, e.g. ACT versus REF. The second approach was to look at correlations between learning styles and cognitive testing results by treating a given scale as a continuum, e.g. ACT at one end of the scale and REF learners at another. Cognitive testing results consist of scores and response times. Scores are measured as the fraction of correct responses to total tasks. Response times are measured as the amount of time, in seconds, elapsed between the presentation of a stimulus and a participant's final response. While it is useful

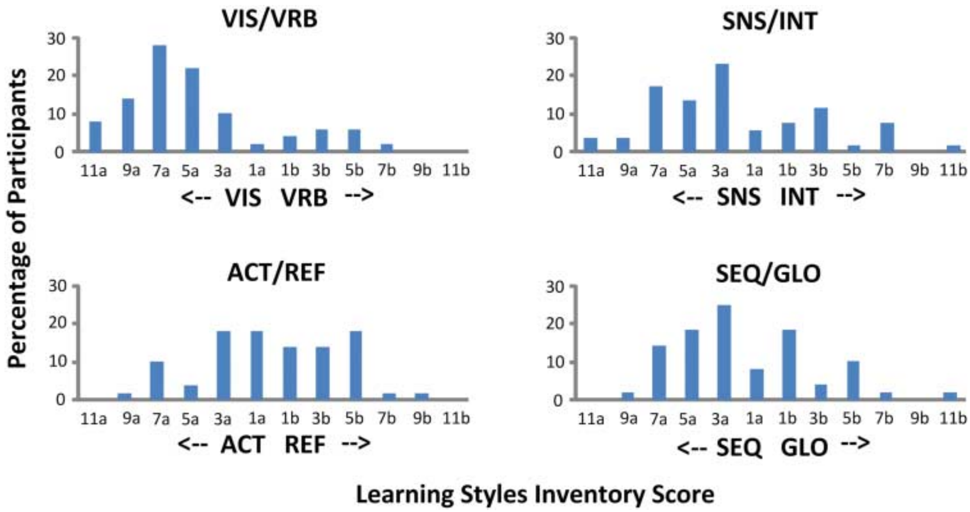

Figure 5. Distribution of learning styles in engineering students.

to determine whether or not task scores are different across learning styles, Felder and Silverman (1988) point out that the FSILS is not a dichotomy, but rather a continuum scale or spectrum. The histograms presented in Figure 5 do not indicate a smooth or even Gaussian distribution across the entire spectrum (ACT versus REF is closest to normal); hence, both correlations and *t*-test comparisons between groups with different learning styles are worth investigating. For a continuous (continuum) scale, the 'a' end of the LSI scale was given a negative sign, while the 'b' end of each scale was given a positive sign. For example, VIS/VRB was given a scale from −11 to 11, with −11 being strongly VIS and +11 being strongly VRB, making a single continuous scale. For dichotomy comparisons, the 'a' and 'b' ends of the LSI scale were both given positive signs, with each end of the spectrum being treated as a single LSI category for comparison between groups. For example, VIS/VRB was divided into VIS and VRB, each with a scale from 1 to 11. These two comparison approaches will be referred to in the results section as *continuous scale* and *divided scale* comparisons.

The results in Figure 5 show a very strong preference by most students for visual learning, and less strong preferences among the three other domains. The distributions are not normal across the scale continuum – as can be seen from the histograms in Figure 5. The distributions look almost bimodal, with only the active–referential scale appearing to peak near the centre of the continuum.

Table 1 gives the percentages of students falling into each category when the learning styles scales are viewed as two ends of the spectrum. Over 50% of the participants favoured active, sensing, visual, and sequential learning styles, with the biggest difference in percentages in the visual/verbal domain and the smallest difference in the active/reflective domain.

Table 1. Total distribution of learning styles in per cent of participants.

ACT	SNS	SEQ	VIS
51%	69%	65%	82%
REF	INT	GLO	VRB
49%	31%	35%	18%

Table 2. Total distribution of learning styles by gender in per cent of participants.

	ACT	SNS	SEQ	VIS
Male	18 (55%)	20 (61%)	21 (63%)	28 (84%)
Female	8 (44%)	15 (83%)	12 (67%)	14 (78%)
	REF	INT	GLO	VRB
Male	15 (45%)	13 (39%)	12 (37%)	5 (16%)
Female	10 (56%)	3 (17%)	6 (33%)	4 (22%)

Table 2 gives the distribution of learning styles broken down by gender, with the numbers shown as well as the percentages given in parentheses (Hames and Baker 2013). In general, the distributions between styles are fairly similar across gender category with the exception of the sensing/intuitive scale, where women show a much stronger skewing towards sensing as opposed to intuitive.

Across gender, the average score for participants in a given LSI category is shown in Figure 6. The figure shows that the average scores were higher for sensing, sequential, and visual learners, meaning that learners on those respective ends of the spectrum were distributed more strongly towards that end of the spectrum. Active and reflective average scores were very similar, and also somewhat low, meaning that most students had a preference for one style or the other, but not a strong preference.

The scores on the FSILS were compared to the scores and response times on the three cognitive tasks using the following methods:

(1) Scores and response times on each sub-task of each cognitive task were compared between learning types within each of the four learning styles scales (e.g. ACT versus REF) using an independent samples *t*-test.
(2) Scores and response times on each sub-task of each cognitive task were correlated with all four continuous learning styles scales. The correlation coefficients were tested for statistical significance.
(3) Scores and response times on each sub-task of each cognitive task were correlated with all eight divided learning styles scales. For example, the visual–verbal scale was broken into visual only and verbal only, and each respective group was correlated with cognitive task scores within that learning styles group.
(4) The above comparisons (1–3) were repeated for gender-specific groups.
(5) An independent samples *t*-test comparison was done to determine whether there were statistically significant differences on cognitive task performance between men and women.

It should be noted that the *t*-tests performed on scores and response times assume normality within a group (e.g. ACT learners scores are Gaussian, REF learners scores are Gaussian, etc.). The sample sizes are small (under 20) for some groups, especially verbal learners. This small sample size can

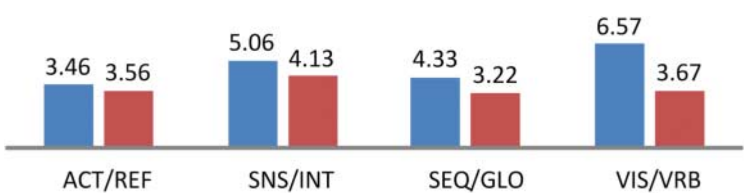

Figure 6. Average LSI scores within each sub-scale.

make it hard to determine normality. A chi-square test was used to check normality for groups because it is commonly used for small sample sizes.

The results of these comparisons, along with task-specific performance results, are summarised in the sections that follow. Table 3 gives a summary of the abbreviations that are used in the charts, tables, and discussion. Scores are reported as decimals with a perfect score being 1 – a score of 0.83 would mean that 83% of the questions for that task or sub-task were answered correctly. Response times are reported in seconds.

Comparison of scores/response times between learning styles

The average scores and response times for the cognitive tasks listed in Table 3 as a function of learning style for the four scales on the FSILS for all 51 participants are shown in Figure 7. The data points marked with stars are those that illustrate points where the differences between scores for the two learning styles are statistically significant, with a p-value less than .05.

Several general trends in the data can be identified. Active and reflective learners scored similarly across all tasks except the MR mirror task, where active learners scored significantly higher. Reflective learners took longer to respond on most tasks, with significantly longer response times on the matrix reasoning and TOL tasks. Intuitive learners scored higher than sensing learners on all TOL tasks and slightly higher on MR tasks. Intuitive learners showed a trend of answering more quickly than sensing learners, but not with any statistically significant differences. Global learners scored higher on MR tasks than sequential learners, with a significant difference on the MR mirror task. Sequential learners had longer response times on all tasks, with a significant difference on the ambiguous matrix reasoning tasks. Verbal learners scored higher than visual learners on matrix reasoning tasks and Tower of London tasks, with a significantly higher score on the verbal-analytical matrix reasoning task. Verbal learners had slightly longer response times on all tasks, but not with any significant differences.

One surprise was the lack of clear differences with statistical significance for sequential versus global learners on the Tower of London tasks. The sequential, stepwise planning required by the task would lend itself to a hypothesis that sequential learners might perform better on the task; however, that was not observed to be the case in this study.

Correlations between scores/response times and learning styles

The average scores and response times for each cognitive task listed in Table 3 were correlated with the scores on each of the four scales on the FSILS for all 51 participants, using both continuous

Table 3. Abbreviations for task types.

Rot	The MR test, including all sub-tasks
Mir	The mirrored MR sub-task
RotD	The depth rotation MR sub-task
RotP	The plane rotation MR sub-task
RotC	The combination depth and plane MR sub-task
TOL	The Tower of London test, including all sub-tasks
TOLE	The easy Tower of London sub-task
TOLH	The hard Tower of London sub-task
Rav	The matrix reasoning test, including all sub-tasks
RVS	The visuospatial matrix reasoning sub-task
RVA	The verbal-analytical matrix reasoning sub-task
Ramb	The ambiguous matrix reasoning sub-task
Score	Total score on a specific task, on a scale from 0 to 1
RT	Response time of a given task for correct answers only, in seconds

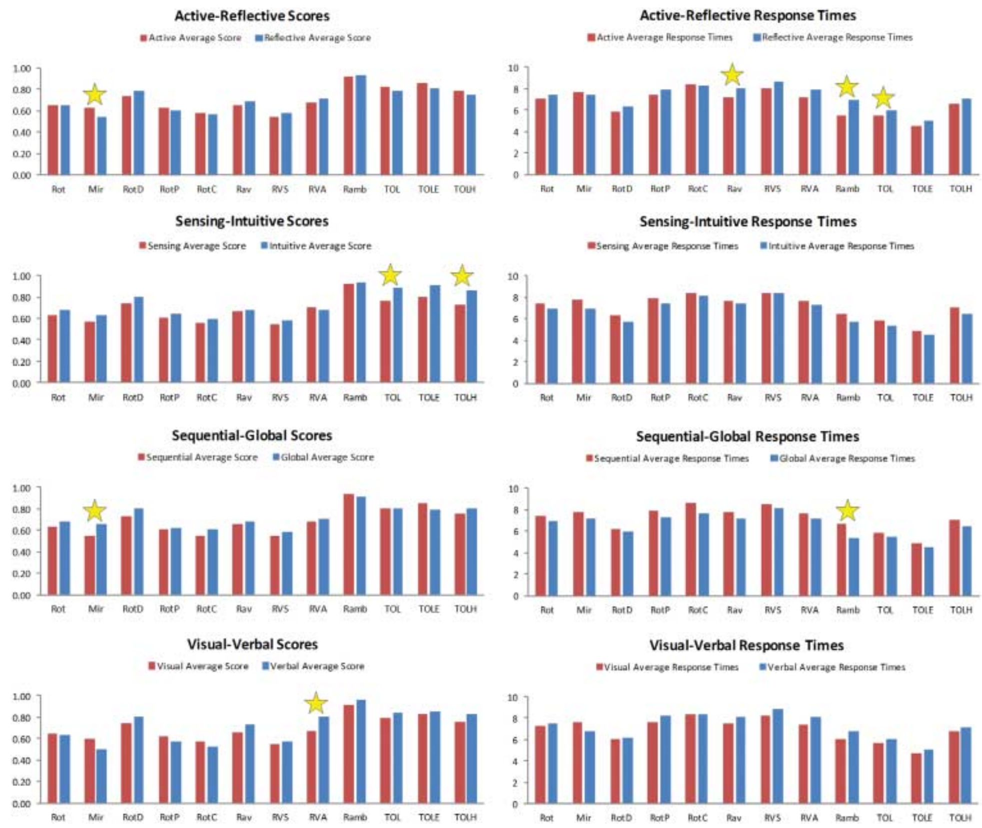

Figure 7. Average sub-task scores (left) and response times (right) for each LSI scale.

and divided LSI scales. A two-tailed *t*-test was used to determine the correlation coefficients that show statistical significance. The results of the correlations that were found to be significant with an uncorrected *p*-value less than .05 are given in Table 4. The divided LSI scales are listed as their respective divisions (ACT, REF, SNS, INT, etc.) and the continuous LSI scales are listed as ACT/REF, SNS/INT, SEQ/GLO, and VIS/VRB.

Table 4 illustrates that there were no significant correlations between learning styles, either for continuous scale or divided scale, and cognitive test scores. There were, however, a substantial number of correlations between response time and learning styles.

A negative correlation would mean a higher score on the learning styles scale results in a lower (faster) response time. For correlations on the divided scales, Table 4 indicates that active learners who score higher on the active learning scale are faster on the visual sub-tasks within the matrix reasoning and on the TOL and TOL-easy tasks. Sequential learners scoring higher on the sequential learning scale are faster on the matrix reasoning, the verbal-analytical sub-scale of the matrix reasoning, and the mirror part of the MR. For the correlations done with a continuous scale across a learning style, the active/referential scale scores show the most correlations with task response times, with positive correlations between learners who are more active on the continuous scale and response times for all scales of the matrix reasoning task and the Tower of London task. Since 'active' is on the negative end of the continuous scale, this means that the more active a learner is on the active/reflective scale, the faster (lower) their response time tends to be. The continuous active/reflective scale yields more results that are statistically significant than the active portion of the divided scale. The active/reflective distribution shown in Figure 5 is the most

Table 4. Correlations between sub-task RT/scores and LSI scales ($p < .05$).

Learning styles category	Measurement	Corr.
ACT	RVS RT	−.440
	TOL RT	−.430
	TOLE RT	−.430
SNS	RotD RT	.451
SEQ	Rav RT	−.358
	RVA RT	−.362
	Mir RT	−.406
VRB	Ramb RT	−.766
ACT/REF	Rav RT	.409
	RVS RT	.363
	RVA RT	.306
	Ramb RT	.329
	TOL RT	.349
	TOLE RT	.351
	TOLH RT	.308
SNS/INT	RotD RT	−.321

Gaussian/normal distribution among the four learning styles scales, indicating a more normal distribution that would be more likely to show correlations that have good statistical properties when considering the continuous scale.

Cognitive task results by gender

The effects of gender were investigated, both to compare men and women across cognitive tests as well as to compare gender-specific correlations between learning styles and cognitive tests. Figure 8 shows the average scores and response times for each gender on each sub-task listed

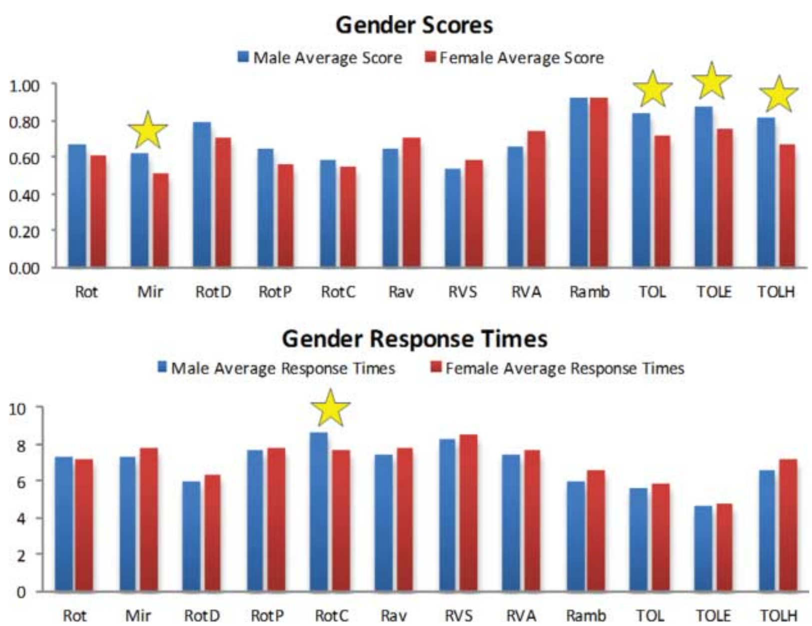

Figure 8. Average sub-task scores and response times across genders.

in Table 3. The sub-tasks with stars over them are the ones that showed statistically significant differences between genders using a t-test with a p-value of .05.

From Figure 8, male average scores were statistically significantly higher than female scores on tasks that involved a high level of visual processing, including all scales of the Tower of London and the mirror sub-task of MR. Female students showed a trend for higher scores on the matrix reasoning tasks; however, the differences only represent a trend and did not pass a statistical test (this is possibly due to the smaller group size for female students).

Cognitive task score differences by learning style for males

The results of a comparison across learning styles differ significantly from those reported for a group including both men and women compared to when the participants are divided by gender. Statistically significant differences between learning styles for men were found for four different cognitive tasks, summarised in Table 5 indicating the following: global learners among male students scored higher on the hard Tower of London tasks than sequential learners, and verbal learners scored higher than visual learners on the verbal-analytical matrix reasoning task, with a p-value slightly higher than .05. As far as response times, reflective male learners took longer to respond on both the general matrix reasoning and ambiguous matrix reasoning tasks.

Cognitive task score differences by learning style for females

For women participants, there was no task that provided statistically significant differences on scores when compared across LSI types. There were statistically significant differences in response times on two tasks. Sequential learners took longer than global learners to respond on the matrix reasoning task and verbal learners took longer than visual learners to respond on the MR in the plane. The results are summarised in Table 6.

Table 5. Male t-test results between sub-task RT/scores and LSI scales ($p < .06$).

Scale	Measurement	Score/RT	p-Value
SEQ	TOLH score	0.762	0.010
GLO		0.917	
VIS	RVA score	0.639	.056
VRB		0.800	
ACT	Rav RT	6.969	.024
REF		8.069	
ACT	Ramb RT	5.162	.010
REF		6.913	

Table 6. Female t-test results between sub-task RT/scores and LSI scales ($p < .05$).

Scale	Measurement	Score/RT	p-Value
SEQ	Rav RT	8.283	.042
GLO		6.805	
VIS	RotP RT	7.429	.037
VRB		9.186	

Correlation between learning styles scores and task scores by gender

The average scores and response times for the cognitive tasks listed in Table 3 were correlated with the four scales on the FSILS for females and males, using continuous and divided LSI scales. Those correlations that were shown as significant ($p < .05$) are given for females in Table 7 and males in Table 8. The divided LSI scales are listed as their respective divisions (ACT, REF, SNS, INT, etc.) and the continuous LSI scales are listed as ACT/REF, SNS/INT, SEQ/GLO, and VIS/VRB.

From Table 7, active learners tend to have active learning styles scores that are negatively correlated with response time across a number of scales, meaning a higher active learning score is associated with a faster response time. Among women, the verbal learning score was negatively correlated with response times for several tasks and was positively correlated with the visual-spatial score on the matrix reasoning task, a somewhat counter-intuitive result.

Referential learning score was positively correlated with depth and combination depth/plane MR tasks. This is also somewhat counter-intuitive, as we might expect active learners to be more

Table 7. Female correlations between sub-task RT/scores and LSI scales ($p < .05$).

Learning styles category	Measurement	Corr.
ACT	Rav RT	−.724
	Ramb RT	−.761
	RVS RT	−.712
	TOL RT	−.904
	TOLE RT	−.831
	TOLH RT	−.785
REF	RotD score	.715
	RotC score	.644
SEQ	RVS RT	−.773
	RotD score	−.598
VRB	RVS score	.970
	Rav RT	−.965
	Ramb RT	−.990
	RVA RT	−.966
	TOL RT	.506
	TOLE RT	.494
SNS/INT	MR RotD RT	−.481

Table 8. Male correlations between sub-task RT/scores and LSI scales ($p < .05$).

Learning styles category	Measurement	Corr.
REF	RVA RT	.601
INT	RotC RT	.620
SEQ	RVA score	.458
	TOL RT	−.434
	TOLE RT	−.446
	Mir RT	−.442
GLO	Ramb RT	.602
	TOLH RT	.653
	Rot RT	.583
VIS	RVA score	.375
ACT/REF	Ravens RT	.452
	RVS RT	.358
	RVA RT	.342

adept at MR tasks, particularly if they are visualising using their hands to do the rotation. This effect was not noticed in males, whose statistically significant correlations are shown in Table 8. Like the results for females and across-gender correlations, learning styles scores tended to be more strongly correlated (or anti-correlated) with response times than with scores on the cognitive tasks. In males, however, there are more correlations on the sequential and global scales across tasks than there were for women, with sequential score strength being negatively correlated with Tower of London and mirror MR response times and positively correlated with matrix reasoning verbal-analytical scores.

Discussion

This section will discuss and interpret the results for each learning style by (1) comparing learning styles with cognitive task performance and (2) examining the differences associated with gender for both learning styles and cognitive task performance.

Active/reflective learning style

Only the mirror rotation task showed significant differences when comparing active and reflective learning styles, with active learners being more accurate on the task. The response time measures show a general trend with active learners having faster response times across all of the tasks, and having statistically significantly faster response times in matrix reasoning and Tower of London tasks. According to Felder and Silverman (1988), active learners tend to be more likely to 'jump in' to a task, while reflective learners like to think things over. The observed longer response times compared with relatively similar accuracy scores on most tasks reinforce the conclusion that reflective learners across cognitive tasks are slower to respond than active learners. This trend is also evident in the correlations between active and reflective learning styles scores and response times across tasks including matrix reasoning and MR sub-scales. The correlations are even stronger when looking at females and include additional correlations with the Tower of London task for women that are not evident when looking at men or combined gender. One possible explanation for this effect is that women who are reflective learners might be more verbally engaged in completing the task. In other words, they might be 'talking through' the task mentally to a greater degree, making the reflective score more strongly correlated with lack of speed for women. As mentioned in the section on results, the reflective score for women was positively correlated with the MR depth and depth/plane sub-tasks scores. This was not the case for men, whose active/referential scales did not correlate at all with the MR task. The response times for women on the MR depth/plane sub-task were statistically significantly higher than those for men on the same task; this was the only task where women were slower than men. One conclusion to draw from the results is that the active/reflective learning style affects women on task speed and performance more than it does men, particularly for tasks that involve a high level of visual-spatial processing to convert from a 2D representation to a 3D visualisation of rotation. In the classroom setting, it may be important to allow sufficient time for reflective learners to process information. The enhanced gender difference might offer one explanation for why women have been observed to be less likely to respond in class – the processing of information occurs at a different pace and level on some types of tasks (Rocca 2010). Lack of participation by female students might be less of a social issue and more of a difference in processing style. An alternative conclusion might be that reflective learners process the information more slowly by choice because they place a greater value on the process of considering all aspects of the problem as opposed to generating an immediate solution or response to the question.

Sensing/intuitive learning style

There were no statistically significant differences on any cognitive tasks between the sensing and intuitive learners, although the general trend was that intuitive learners were slightly more accurate and faster on most tasks. This learning styles scale was also not well correlated with any of the cognitive tasks. There were some correlations with MR response times, but there was no clear pattern. Our tasks were not designed to measure skills that would be closely related to either intuition or sensing, hence any observed relationships would be expected to be relatively weak.

Sequential/global learning style

The sequential/global scale was the one scale where we hypothesised that we would see some of the biggest differences between learning styles in cognitive task performance. The Tower of London tasks were expected to measure a level of planning that we believed would be stronger in individuals whose learning styles preferences tended towards sequential, stepwise thinking as opposed to global, 'big picture' thinking. In fact, global learners scored higher on MR tasks and were faster on all tasks when a group-wise comparison was done between global and sequential learners. On the other hand, sequential learning scores were negatively correlated with response times on the matrix reasoning, matrix reasoning verbal-analytical, and mirror rotation tasks, meaning that sequential learners were faster if they had a stronger sequential score. This is a seeming contradiction. There are two possible explanations for this. One is that the distribution across the full global–sequential scale appears highly non-Gaussian, while within a given side of the scale the distribution approaches a more Gaussian shape. This would result in a greater degree of reliability of statistical comparisons within one end of the spectrum compared to one across both ends of the spectrum. Another explanation might be that there are very different characteristics between a sequential learner who is strongly sequential compared to one who has weaker sequential preferences. Sequential learning in engineering is of special importance because engineering courses commonly emphasise stepwise approaches to problem solving. The global–sequential learning scale is one that deserves further study and research to determine the relationship between learning styles on either end of this spectrum and performance in a classroom environment. Based on the results here, global learners are expected to have strong performance on visual-spatial, executive, and analytical reasoning tasks, which would predict strong performance in classes requiring these skills.

Among women, sequential learning scores are strongly negatively correlated with the matrix reasoning visual-spatial response times and with MR scores. A higher percentage of women are sequential learners in our study, thus women in engineering school might be more likely to be sequential learners. They would most likely not perform as well in classrooms requiring skills like those used in MR: motor rotation, 2D to 3D visualisation, and planning of movement. This raises the question of whether 3D visualisation and simulation might be effective in mitigating the gender and learning style differences in engineering school that are a result of difficulty with visualising 3D objects from 2D schematics.

Visual/verbal learning styles

A discussion of the visual–verbal learning style should be prefaced with the fact that verbal learners make up a small percentage of the overall group (16% of men, 22% of women, and 18% overall), which could impact results. The distribution of learning styles scores appears very close to a bimodal distribution, looking Gaussian on both the visual and verbal sides of the spectrum. With this in mind, results indicated that verbal learners tended to score higher on the matrix reasoning and Tower of London tasks, and lower on the MR task (the more visually oriented tasks). *T*-test comparisons with the male group show that verbal learners score statistically significantly higher on the matrix reasoning verbal-analytical task than visual learners. The comparison between visual and verbal women showed differences in response times in MR (in the plane) with verbal learners being slower to complete the task. Once again, when comparing gender groups, learning style differences in women tend to contribute more significantly to reduced processing speeds in certain tasks, particularly MR tasks. Among women, verbal learners have verbal scores that are very strongly negatively correlated to response times in the matrix reasoning tasks and positively correlated to response times in MR tasks. The matrix reasoning task involves analytical reasoning and working memory functions that emphasise the strengths of verbal learners – the ability to self-talk and use language as an asset in reasoning and memory.

Conclusions

This study attempted to determine the relationships between learning styles as measured by the FSILS and cognitive performance on three tasks. As described throughout the paper, a number of correlations were found within groups and statistical differences were found between groups when comparing performance of learning styles on different cognitive tasks. The global–sequential, active–referential, and visual–verbal scales all have significant results that indicate that these learning styles are related to performance. Most of these differences were found in response times, not accuracy. This might explain the inconsistency of previous studies that looked at assessment scores without considering processing speeds. While response times may not influence test scores or accuracy, they can definitely change students' quality of the experience in a classroom. When learners are slower to process certain tasks, particularly verbal analytic reasoning tasks and MR tasks, frustration may occur. On the other hand, in many engineering situations, a slower response can indicate greater attention to strategic planning and problem formulation, both of which are very useful in the engineering practice. Simple cognitive tasks may not provide an accurate measure of performance on the more complex, elaborate problem solving involved in the engineering analysis and design process. However, these tasks do measure skills often applied in the engineering classroom setting, such as interpretation of schematic diagrams, design of 3D mechanical systems, and visualisation of antenna patterns in 3D. Incorporating analytical reasoning and adding verbal cues into the curriculum may make the material more attractive to those with learning style and cognitive processing differences. The global–sequential scale in particular deserves further research, as there were a number of differences found across this scale, and both thinking styles are clearly useful in the engineering problem-solving and design approach.

There were also a number of gender differences noted in the study. There were stronger correlations among females between learning styles and processing speeds on certain tasks, and the correlations were different for females than for males. In the classroom, this could imply that a different approach to the impact of learning styles for women might be beneficial. For example, the use of technology to enhance 3D visualisation and other skills that require visual processing speeds might serve to reduce differences in performance, speed, and level of frustration among students of different learning styles, including across gender groups. Class discussions that allow for carefully thought-out responses and the use of descriptive language in addition to figures and charts might also be beneficial to some students, allowing for strong verbal skills and sequential learning styles to serve as an asset. This could serve to increase the diversity of engineering students by reducing frustration for students possessing different learning strengths.

The participants involved in this study, though all attending an American university, came from a diverse background. Without an accurate record of their nationalities and languages, the results should not be generalised to students from other countries. The participant sample included numerous engineering types, grade levels, and learning types. The goal of this research was to observe the relationship between learning styles and cognitive abilities in engineering students without a focus on a specific engineering type or grade level. Though the engineering types and grade levels may be skewed and unrepresentative of the Engineering College, the cognitive tasks tested skills needed in most engineering courses.

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Conflict of interest

The authors declare no conflict of interest.

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