Investigating mechanical engineering students' design ability using learning styles

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ABSTRACT: Engineering design (ED) is a core process in mechanical engineering, where new ideas and concepts are created and transformed into a product or system that satisfy requirements and constraints. Using scientific and mathematical principles, ED students apply science ability, sociological sense and tactical ability to a product. Different learning strategies, intellectual development levels and learning styles affect ED outcomes. In this study, the author investigates how the design ability relates to spatial visualisation learning ability, which decisively contributes to success in engineering. Students' learning styles were compared and analysed using an empirical study involving 357 students from the University of Ljubljana and Cracow University of Technology. Confirmatory factor analysis revealed that visual learning preference along with sequential thinking and a need for structure significantly ($p < 0.001$) predicts design ability. Effect size of ED might be enlarged with global divergence motivated by others to include a sociological sense. Female and male students had similar levels of spatial visualisation skills for ED abilities.

INTRODUCTION

Engineering design (ED) as a key engineering outcome, contains all the organised information necessary and sufficient to build, maintain and, eventually, to demolish engineering objects or systems to recover material, and it includes design concept and detailed design [1].

A design concept represents the qualitative or abstract part of ED, which is more symbolic and includes more novelties, while detailed design represents the quantitative or concrete part, where the attributes are described numerically, and rather than applying a novelty approach, analysis and optimisation are applied. Within ED context-mapping, several requirements and constraints are used to fulfil a need of the customer (society) or due to technological changes in the real world, to meet the needs at a higher or at specific level [1]. The innovation and customer service skills of designers are crucial for success of competitive projects [2].

Since ED is about both creation and design [3], many believe that spatial reasoning and visualisation ability contribute to success in ED through science, sociological and tactical ability development [4-6]. Only a well-built structure (high task structure) with defined requirements and constraints might increase creative ability [7][8]. ED ability is …*a key human factor in product innovation and the progress of human society* [6]. ED is very complex, thus, good designers must possess highly-developed science ability in terms of subject matter declarative knowledge, procedural, schematic and strategic knowledge with the ability to apply and transfer knowledge using analytical and open-ended problem-solving skills [9].

To scaffold the ED process, many suggest learning styles as a tool to map and to ameliorate students' differences and consequently increase the ED ability [4][8][10][11]. Learning style as a component of the wider concept of personality should be used as a method to achieve the best learning results [12]. For the purpose of this study, a recently developed dynamic learning style inventory (DSLI) was used as an extension of the research done by Avsec and Szewczyk-Zakrzewska [4]. DSLI is able to measure learning styles on eight modules at a time as a holistic or single category measurement.

Further, several ED course designers use different approaches, methods and strategies to improve ED outcomes. To create an effective design team, the methods of *Belbin's Team Roles* and of *TRIZ* in the context *of the Kolb and Felder-Silverman models* are mostly used for real-world problem-solving in engineering students at the University of Ljubljana. The basic motivation of this research was to offer some new insights about spatial visualisation ability as an ED core ability through learning style mechanisms. The purpose was not only to introduce DSLI as a knowledge enhancer and diffuser, but also to provide engineering course designers with a tool to design learning style-based spatial instruction to enhance students' social and tactical ability.

Engineering Design and Design Ability

ED is regarded as the peak of creative engineering activity; its results are often the absence of some effect rather than the presence of some observable feature. ED is creativity, consumes resources (information, material, energy), has a purpose, and can, therefore, be assessed and evaluated. The broadest definition of ED is *…to design is to formulate and execute a plan to satisfy a need* [13]. With ED, a reduction of uncertainty theory is applied following characteristics of ED [13]: 1) design problems are always subjected to certain conditions; 2) conditions as benchmarks for final decision making about the solution; 3) a design problem is very often a decision-making problem; 4) information management is crucial to reach a satisfactory solution; 5) a design problem is a real-world problem. The needs are met on the physical plane; 6) design problems do not have a single response; and 7) design theories have a high degree of abstraction and the best solution is as an ideal design, which is achieved by systematically applying advance design theories.

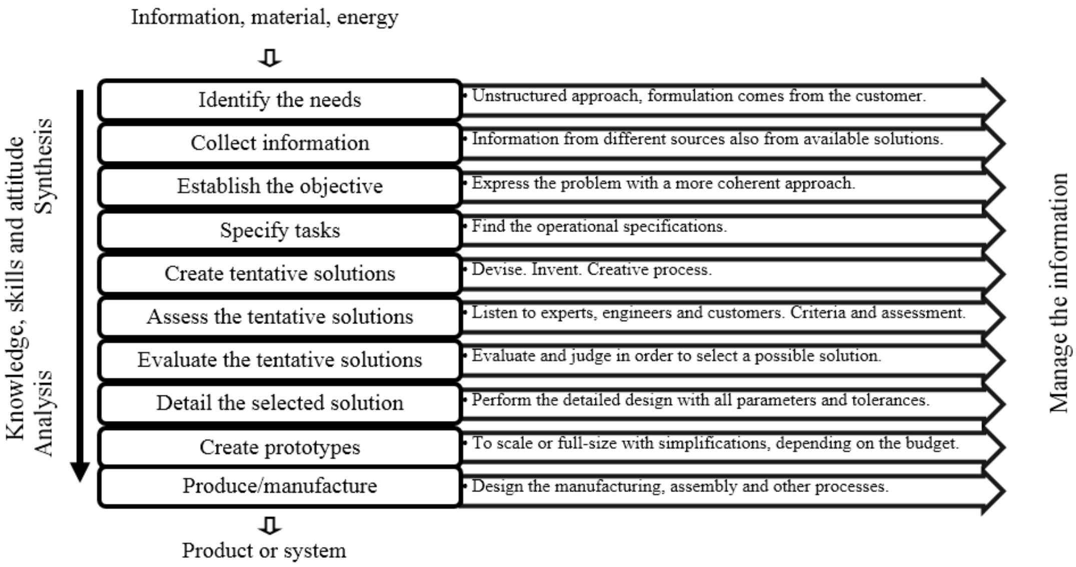

Figure 1: Core design activities arranged sequentially.

Figure 1 depicts ED as a very complex process and as such, it requires several, very different sets of knowledge, skills (cognitive, technical, interpersonal) and attitudes. To assess an engineer's design ability, one should first refer to cognitive theory. The ED process is an interaction between creative synthesis and analytical evaluation [13]. During creative synthesis, the right brain is activated to perform irrational, uncritical thinking, illogical, divisive motor skills may be at play and many alternatives without rules emerge. During analysis and decision making, the left brain is used to apply rigid rules, critical and logical thinking, and rational (sense), converge ideas and concepts, to obtain one single answer to a real-world problem.

ED ability consists of several abilities. Firstly, one should point to the science and engineering subject matter knowledge of declarative (*know that*), procedural (*know how*), schematic (*know why*), and strategic (*know when and where*) cognitive ability as a view for total engineering [14]. Schematic and strategic knowledge domains along with skills and attitude are parts of tactical ability (logical and analytical abilities) for critical thinking and decision-making.

Every designer must have a sense of sociology, which can be graded into three levels [6]: 1) associative sense (meet the needs of customers); 2) broader sense (offer more extra/specific use of a product); and 3) futuristic sense (think beyond the customer's needs). As a part of sociological ability, interpersonal, communication and team skills are important [9]. Information management and leadership through ED also claim wider competence or ability for organisation, research, leadership, etc, from a good designer. Beside the aforementioned abilities, a design engineer possesses an attitude towards nature and society in the sense of cognitive opinions about design, to express emotions and feelings (affective), to show inclination for action (conative), and to demonstrate positive or negative responses to stimuli (evaluative). The emotional and environmental part of the ability approach should be decisive at creative design development [8].

According to a number of studies, spatial ability (SA) seems to play a crucial role in information and communications technology-enhanced learning in engineering [3][5][9][11][15] and it is often defined as the ability to rotate or fold objects mentally, and to imagine the changes in location and form due to this manipulation [5][15]. Spatial ability consists of five sub-dimensions - spatial visualisation, spatial relations, closure speed, closure flexibility and perceptual speed. Spatial visualisation, for instance, involves the ability to imagine spatial movements of objects and shapes [16].

SA should be demonstrated through drawing, sketching, computer aided-drawing, design and manufacturing, recognising kinematics or performing other mental rotations in 2D or 3D reality [5][9][16]. Spatial abilities are determined in three key operations that designers, engineers and many other professions need to perform: capability for blueprint reading where a 3D mental representation has to be built from orthographic projections, and the reciprocal skills, deriving multi-view drawings from real or imaginary 3D objects [15], and having capability for 3D print visualisation and reading both object and layer-based structure [13].

SA is very important for static pictures/drawings or objects, where high-spatial able students (highly developed visualisers) benefit, while dynamic learning objects offer opportunities to increase SA of both low- and high-spatial able students/designers [16]; especially, for the mapping function, to form using instructional media/animations and simulations [17]. It seems that only higher abilities concerning spatial rotation and control might make a difference at static drawings transfer to runnable mental model [16].

Learning Styles in Engineering

Learning style is a generic concept that frequently includes cognitive styles, personality styles, emotional and sociological styles, sensory modes and different typologies [12]. According to the comparison of different learning styles models, Avsec and Szewczyk-Zakrzewska have prepared a composite called DSLI, which consists of eight modalities: 1) learning orientation; 2) information processing; 3) understanding/thinking; 4) perceiving information; 5) physical and time orientation; 6) sociological orientation; 7) emotionality; and 8) environmental features [4]. With DSLI, one can successfully cope with all ED abilities to reveal differences in students' learning preferences.

Nevertheless, additional importance of learning styles was revealed. In an earlier study and in many others, predicting validity of learning styles to forecast academic success and creative ability of students could be found [8]. Considering academic fields or disciplines, different learning styles allow students to be successful in the field. Mechanical engineering students are pragmatic, sequential learners where facts dominate [4][10]. Mostly they are convergent thinkers with a sensing learning style of perceiving information. Being self-motivated, having visual physical preferences [4], being concrete sequential learners, being self-effective and being responsible have been found to be important positive predictors in the grade point average (GPA) [8]. Concrete random (active), extraverted, other-motivated learners with a need for authority and structure, test anxiety, and with procrastination behaviour might have a negative correlation with GPA [8].

Also reported have been findings on how learning styles predict creative achievements as an outcome. Divergent thinking, openness to experience and intellect predict creative achievements in science and engineering. Active learners do not need a structure, but need a lot of space for acting and as global learners see the whole picture with overlapping parts. Nonverbal behaviour during ED work or other collaborative learning significantly predicts creativity. Significant negative associations were found between abstract sequential learners and the creativity constructs fluency and originality. Nonconformists, extroverted and mastery goal-oriented learners positively contribute to creativity, as do learners with a disciplined imagination, with awareness of others and inquisitive learners. Acceptance of authority and a need for structure are negatively correlated with a creative gain.

Considering the fact that ED is close to creativity, it will be interesting to find relations with predictive validity of learning styles in ED. Therefore, the purpose of the present study was to investigate whether engineering design ability is related to specific cognitive styles; namely, spatial and object cognitive styles. More specifically, one can address the following questions:

- What are the learning styles employed by spatial and object visualisers in engineering design?
- How does engineering design ability differ across gender?

For this research, the recently developed DSLI was used, which was administered during several study programmes in mechanical engineering, where University of Ljubljana students were mostly from the ED study programme, while Cracow University of Technology students were from industrial mechanical engineering and energetics study programmes.

METHOD

Sample

The sample for this study consisted of undergraduate and graduate students enrolled in mechanical engineering courses from Cracow University of Technology, Poland and the University of Ljubljana, Slovenia. With the permission of, and assistance from, the instructors who agreed to have their students participate in the study, a paper and pencil survey was distributed.

Of the 365 enrolled students, 357 completed the survey entirely (2.2% missing values, n = 8). The number of respondents in this study fulfilled the requirements of exploratory factor analysis (EFA) with 25 independent variables in which at least 125 participants are needed to make confident assumptions about any observed relationships [18]. There were more male respondents (84%) than female respondents (16%). Respondents were between the ages of 18 and 34 years old. More than half of the respondents took undergraduate-level courses. Students from the University of Ljubljana represented 46.2%, while Cracow University of Technology students comprised 53.8%, of the total.

Instrumentation

The survey included questions on demographics, 71 questions on eight modes of predictor variables with 25 subscales and self-reported GPA as the cognitive variable. Demographic questions covered gender, age and course level. This study adopted a self-developed instrument. Instrument development was involved for all eight modules and language version (Slovene, English and Polish). For the assessment, a 6-point phrase completion scale was used. The new scale successfully substitutes and eliminates all limitations of the existing Likert scale. The intervals of the scale together form a continuous type, from 0 (*very unlikely*) to 5 (*very likely*). It does not present the mean, but ensures the comparability of continuous responses and produces better assumptions of parametric statistics while avoiding bias.

As an instrument, the dynamic learning style inventory (DSLI) was used which successfully enables valid and reliable measurement of learning styles as a whole or each module separately [4]. For the purpose of this research, only 25 subscales were used with 71 items in total (2-4 items per a subscale).

DSLI was moderately reliable with Cronbach $\alpha = 0.72$ (standardised items' Cronbach $\alpha = 0.78$). All 25 subscales were tested on discrimination ability (sensitivity of instrument) and majority of discrimination index r_{pbis} values are in optimal range $0.2 < r_{pbis} < 0.6$, while five values of 0.10's are still acceptable [19] for measuring what they are designed for.

Procedure and Data Analysis

The researchers contacted instructors in Slovenia and Poland about their willingness to include their students in this survey. A paper and pencil method was utilised by interested instructors to distribute the survey. Students participated in the study during real-world classroom sessions throughout a study day. Administration of the survey was performed from March 2015 to April 2015, depending on the activity plan. A high response rate was obtained because of the direct presence of teachers or instructors and survey administration.

Data analysis was conducted using SPSS and AMOS software. To support the criterion-related validity of the test, a corrected Pearson r_{xy} coefficient was used. A corrected Pearson r_{xy} coefficient is an appropriate measure of criterion-related validity, which served to verify concurrent and predictive validity [20]. For the purpose of this study, convergent and discriminant validity were assessed by performing an EFA. However, two criteria were considered to ensure an appropriate sample size was obtained for the current study to enable factor analysis to be undertaken: a) Kaiser-Meyer-Olkin (KMO) sampling adequacy; and b) factor loadings and the correlation between a variable and a factor [18]. To demonstrate convergent validity, magnitude of the direct structural relationship between the item and factor should be statistically different from zero [18]. As for discriminant validity, factor correlation matrix analysis has been employed in this study. This method checks the estimated correlations between the factors.

Descriptive analyses were conducted to present the student basic information and the average score of learning style variables. A multivariate analysis to find and confirm significant relationships across gender with an effect size was carried out. The measure of the effect size is partial eta squared. Also, a confirmatory factor analysis (CFA) using AMOS software to assess measurement model validity was conducted, where the spatial visualisation ability is an enhancer-promoter in engineering design.

RESULTS

Validity

Correlation analysis of subscales revealed a low value of the Pearson correlation coefficient ($r_{xy} < 0.34$), demonstrating that all subscale items were solidly designed and constructed, and each subscale was measuring exactly what it was designed for. Evidence of high criterion-based validity was provided; therefore, the high concurrent and predictive validity of the results was verified [20].

EFA provided evidence of construct validity of the model variables. Construct validity was first tested with extracted variance (communalities) and all aggregated subscales' items are able to extract variance of $h^2 > 0.5$ (Table 1), representing high construct validity [18]. To ensure an appropriate sample size to undertake factor analysis, the value of KMO sampling adequacy on the survey and test was 0.81 and Bartlett's test of sphericity was significant ($\chi^2 = 1725.81$, $df = 300$, $p = 0.00 < 0.05$). The sampling adequacy value of 0.81 for the model variables was very good [18].

On the first-run maximum likelihood estimation (MLE), the total variance of the model factors was 61% (nine factors, eigenvalue >1). The decision to eliminate low-loading variables was confirmed using guidelines by Stevens [18] of statistical significance for interpreting factor loadings. Guidelines are based on sample size and suggest that the statistically acceptable loading for 357 participants is 0.26. The structure matrix revealed valid variables, which provide evidence of the convergent validity of the factors. A factor correlation matrix was also calculated, where there were very low correlation values between seven factors and correlations did not exceed 0.45 < 0.7. These factors are distinct and uncorrelated, which shows the high discriminant validity of the factors [18]. A valid pattern matrix obtained with MLE with the promax (Kaiser normalisation) rotation method present loadings of nine factors and was further used in CFA.

Descriptive Statistics

Table 1 depicts the average scores on the subscales, where there is *M*-mean and *SD*-standard deviation. Statistically significant differences ($p < 0.05$) in learning styles across gender are marked in italic. Levene's test confirmed that the study sample did not violate the assumption of normality, which confirmed that the sample is normally distributed ($p > 0.05$). MANOVA tests of between-subject effect revealed significant differences across gender in learning orientation, processing information, thinking, perceiving information, spatial visual ability, sociological preferences and emotionality. Environmental preferences seem to be equally perceived by both female and male students. Effect size is small-to-medium (partial eta squared is 0.02-0.06).

Table 1 shows that mechanical engineering students are still concrete learner where facts dominate. Surprisingly, the large number of theorist learners reveals that mechanical engineering enrol sequential thinkers who are very important for engineering design. Gender differences in learning styles are also shown in Table 1. Female students are more theoretical and abstract learners, with a high ability to reflect. Sequential thinking is useful in tactical and analytical ability development as an important engineering design dimension. Surprisingly, female students prefer to learn alone, something might decrease sociological sense needed for competitive design. Female students are more persistent than male students, but they need structure for learning and problem-solving. The need for structure is associated with a preference for well-ordered situations and tasks through e.g. explicit manuals, rules, direction and criterion-based design tasks. Students with a higher need for structure might perform more creatively when a design task is presented as structured (high task structure) rather than unstructured (low task structure). Female students as visualisers might possess more SA, but it can be markedly utilised only at static drawings and graphics.

Table 1. Average score on subscales on mechanical engineering students' learning styles with a mid-point 2.5. Sample of $n_{female} = 57$, $n_{male} = 300$. Significant differences ($p < 0.05$) are marked in italic. Communalities h^2 as extracted variance.

Module/dimension	Subscale	Total		Female		Male		Communalities h^2
		M	*SD*	*M*	*SD*	*M*	*SD*	
Learning orientation	Concrete (pragmatist)	3.82	0.73	3.66	0.74	3.85	0.73	0.58
	Abstract (theorist)	3.44	0.69	*3.63*	*0.69*	*3.40*	*0.69*	0.54
Processing information	Active (impulsive)	3.02	0.76	2.87	0.80	3.04	0.75	0.58
	Reflective	3.25	0.80	*3.46*	*0.75*	*3.22*	*0.81*	0.51
Understanding/ thinking	Sequential	3.53	0.56	*3.67*	*0.53*	*3.50*	*0.56*	0.66
	Cluster	3.29	0.66	3.38	0.56	3.27	0.68	0.65
	Global	3.57	0.81	3.71	0.65	3.54	0.84	0.56
Perceiving information	Intuitive	2.23	1.04	2.35	0.98	2.21	1.05	0.81
	Sensing	3.98	0.72	*4.18*	*0.69*	*3.94*	*0.72*	0.53
Physical and time	Auditory	3.13	0.72	3.03	0.73	3.15	0.72	0.68
	Visual	3.52	0.64	*3.68*	*0.64*	*3.49*	*0.63*	0.68
	Tactile	3.39	0.75	3.43	0.85	3.39	0.73	0.67
	Kinaesthetic	3.73	0.79	3.77	0.72	3.72	0.81	0.57
Sociological	Learning alone	3.37	0.97	*3.76*	*0.86*	*3.29*	*0.97*	0.63
	Peer oriented	3.21	0.91	3.19	0.97	3.22	0.90	0.73
	Authority figures present	2.91	0.81	2.86	0.78	2.92	0.81	0.59
Emotionality	Self-motivated	3.75	0.83	3.82	0.82	3.74	0.83	0.59
	Other-motivated	4.02	0.74	4.15	0.65	4.00	0.76	0.55
	Persistent	3.58	0.74	*3.84*	*0.69*	*3.54*	*0.74*	0.55
	Responsible	3.55	1.65	3.69	0.92	3.53	1.75	0.52
	Needs structure	3.67	0.69	*4.05*	*0.58*	*3.60*	*0.69*	0.61
Environmental	Sound-acceptable	1.96	1.36	2.25	1.32	1.90	1.36	0.63
	Light-requires much light	3.33	0.98	3.44	1.10	3.32	0.96	0.53
	Needs cool environment	3.22	1.02	3.15	1.30	3.23	0.96	0.65
	Seating design-informal	2.13	1.27	2.37	1.37	2.08	1.25	0.64

Analysing Fit of the Measurement Model

In CFA, a researcher specifies which variables go together, and are assigned to a factor, thus, yielding a *pattern* matrix. CFA models provide strong evidence regarding the validity of a set of measured variables and the theories underlying the structure [21]. A pattern matrix is obtained from EFA using MLE of promax rotation, and it served as an input to pattern matrix builder of AMOS software. In the CFA method, the fit of the factor structure can be verified with several indexes. Chi square (χ^2) describes the difference between the theoretical and measured covariance matrix. The interpretation of the χ^2 - value is ambiguous and depends on sample size. For larger sample sizes (more than 200) the significance level (*p* value) of the test remains significant ($p < 0.05$). So, model fit should be assessed using other indexes as well [21]. The comparative fit index (CFI) and Tucker-Lewis indexes (TLI) compare model fit to the independence model. In this study, the cut-off value of good model fit for both CFI and TLI was 0.90 [21], while the minimal acceptable value is 0.80 [22]. The root-mean-square error of approximation (RMSEA) indicates model fit in comparison with the degree of freedom of the model. A cut-off value of close to 0.08 indicates good fit of the model [21]. Root-mean-square residual (RMR) indicates the model fit by comparing the averages of standardised residuals of the observed and predicted covariance matrixes. A cut-off value of close to 0.08 indicates good model fit [22].

The parsimony goodness-of-fit index (PGFI) and the parsimonious normed fit index (PNFI) are suggested to adjust data of a complex model [21][22]. The PGFI is based on the goodness-of-fit index (GFI) by adjusting for loss of degrees of freedom. The PNFI also adjusts for degrees of freedom, but it is based on the normed fit index. Both of these indices seriously penalise for model complexity, which results in parsimony fit index values that are considerably lower than other goodness of fit indices. Threshold levels have been recommended for these indices within the 0.5 region [21]. Schumacker and Lomax [21] and Hu and Bentler [22] strongly recommend the use of parsimony fit indices in tandem with other measures of goodness-of-fit. The probability of close fit (PCLOSE) has to be greater than 0.05 for the model to be acceptable [21].

EFA identified nine factors and the first CFA model was constructed according to the theoretical factor structure. As expected in the first analysis, the model fit was not acceptable. After the sixth run and reduction of factors to four latent factors (43% of variance explained), which represent mechanical engineering students' ability, and after conducting attenuation correction to remove a correlation coefficient from the weakening effect of measurement errors, the final model was obtained, with the following indexes: the overall absolute fit measures in this research were $\chi^2 = 230.36$ ($p < 0.05$); and the degrees of freedom were 109, which indicate $\chi^2/df = 2.11$, and a ratio of less than three is considered a good fit [21]. The value of RMSEA was 0.05, RMR was 0.04, PCLOSE was 0.17, the value of GFI was 0.93 and the adjusted goodness of fit index (AGFI) was 0.91, which indicated a good fit. The value of CFI = 0.90 and TLI = 0.87, while the parsimony-adjusted measures were PCFI = 0.72 and PNFI = 0.65 what indicates a good model fit. The model fit indexes above showed that the model (Figure 2) of this research is acceptable.

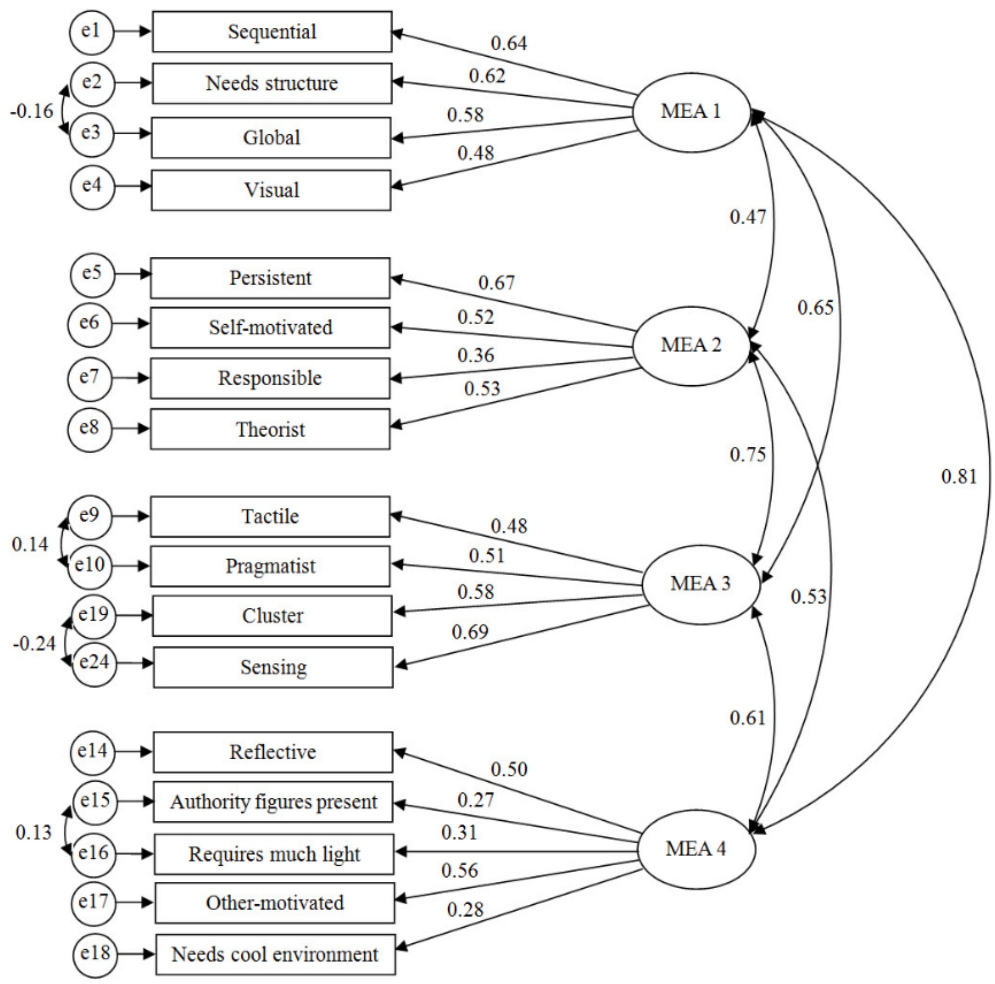

Figure 2: Mechanical engineering students' ability (MEA1-4) factor structure of the compressed learning styles measurement obtained after 6th run and attenuation correction. All model path coefficients are significant ($p < 0.001$).

Spatial visualisation core ability is firstly reflected in factor MEA1 where visual learning style appeared. Sequential thinking is the strongest ability and is needed for tactical dimension of engineering design. Visual and sequential thinkers have a strong need for structure, e.g. explicit directions, rules or learning context set by the environment. To catch the broader context of design activity, they also need associative and futuristic sense and with random thinking ability in order to succeed. Factor MEA1 is strongly correlated with factor MEA4 (correlation 0.81) and design engineer as other-motivated have the ability to connect customers for new or redesign of products with added value.

As a reflector, a designer is able to think beyond the user requirements and anticipate their needs for the future. Designers need authority rather than peers or to learn and to design alone. Product performance meets all requirements of the authority, but this level designer will not be able to add competitiveness to the product. As sequential thinkers, they are left-brain oriented dominantly and need much light on their work. Being motivated by structure is typical for good design engineers, especially, for tasks with constraints and with well-formed structure, which enhances creativity (or not), these designers should develop their engineering knowledge, design skills and creativity at the same time. The need for structure as a stimulant serves as a context mapping enhancer. On the other hand, these students might not be successful in design activities with open problem-solving or at tasks with no constraints. Factor MEA1 reveals that enrolled students are mostly assigned constrained problem situations or in design activity they can choose real-life own problems. Calculating the GPA of students with learning styles of factor MEA1 and MEA4 a score of 7.8 was found for students with high spatial visualisation ability.

Factor of MEA2 and MEA3 are typical mechanical engineer descriptions, which provide efficient solutions to the development of processes and products as persistent, self-motivated, responsible, thinking and doing as convergent thinkers. As sensing learners tend to like learning facts, are patient with details and good at memorising facts, they are more practical; they like to work with real-world problems, but do not like to risk. Surprisingly, quite a number of theorists are enrolled in mechanical engineering study. These students have the higher logical and analytical abilities needed also for tactical dimension of engineering design ability.

Analysing the gender issue, female students significantly ($p < 0.05$) differ from their male counterparts at the following design ability dimensions of learning styles: visual ($M_f = 3.68$; $M_m = 3.48$), sequential ($M_f = 3.67$; $M_m = 3.50$), need for structure ($M_f = 4.05$; $M_m = 3.60$), and reflective ($M_f = 3.46$; $M_m = 3.22$). At the same time, female students are more persistent ($M_f = 3.84$; $M_m = 3.54$) and prefer to learn alone ($M_f = 3.76$; $M_m = 3.29$). The average value of female students' GPA is higher than of their male counterparts (8.4 and 7.7, respectively). All these results relating to gender differences should be considered cautiously due to unequal sample sizes. Perhaps some differences might be expected in favour of female students for responsibility and at global thinking style, while for reflective preference and preference to learn alone, no differences are expected across gender.

CONCLUSIONS

This study was conducted in light of the limitation that students were not evenly distributed according to gender, but the study followed the nature of mechanical engineering study, with the present study yielding some interesting results. These results could be important for design and performance of mechanical engineering spatial instructions.

Spatial ability was found to be a core ability in mechanical engineering students. It serves as an enhancer of high structured design tasks, while for tasks with dynamic learning objects (animations, rich runnable graphics and augmented reality) it serves as a compensator, when both low- and high-spatially-able students advance. Spatial visualisers with high sequential thinking (tactical ability), assigned with high task structure and possessing high random thinking skills (social ability) might be able to produce advanced engineering design.

A design team supplied by high reflectors with extrinsic motivation might meet the needs of society at a higher level. DSLI as an enhancer and knowledge diffuser might provide advanced and innovative engineering design and could ameliorate gender differences. Thus, one can improve retention of female engineering students and increase the enrolment of high spatially able female students at the outset, in order to improve team design ability.

Several spatial instruction designers will benefit from this study to produce more learning style based innovations with inclusion of spatial strategies as a part of the mix approaches for engineering problem-solving. The gender issue is still underestimated due to the nature of engineering and future investigations should go in that direction.

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