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Enhancing Undergraduate Engineering Students' Spatial Skills Through a New Virtual and Physical Manipulatives (VPM) Technology*

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Spatial skills are fundamental to learning and developing expertise in engineering. This paper describes a new virtual and physical manipulatives (VPM) technology that this research team recently developed to enhance undergraduate engineering students' spatial skills. This technology consists of ten manipulatives spanning a variety of levels of geometrical complexity. Each manipulative is authentic due to its real-world engineering applications that were chosen to stimulate student interest in engineering. A computer program was developed to connect virtual and physical manipulatives, allowing students to receive spatial training anytime, anywhere through the Internet. Quasi-experimental research, involving an intervention group (n = 37) and a control group (n = 34), was conducted. Each group completed a pre- and post-test using the same assessment instrument that measured students' spatial skills. Normality tests were conducted. The results show that the data involved in the present study did not have a normal distribution. Thus, non-parametric statistical analysis was performed, including descriptive analysis, correlation analysis, and Mann-Whitney U tests. The results show that the mean value of normalized learning gains is 41.2% for the intervention group, which is 33% higher than that for the control group (8.2%). A statistically significant difference exists between the intervention and control groups in terms of normalized learning gains ($P < 0.01$). The new VPM technology developed from the present study has a medium effect size (0.34) on improving students' spatial skills.

Keywords: spatial skills; undergraduate engineering students; new virtual and physical manipulatives (VPM) technology

1. Introduction

1.1 Importance of Spatial Skills

Spatial skills are a person's mental skills of imaging an object's spatial orientation, or imaging what the object looks like from a certain spatial viewpoint. In some literature [1, 2], spatial skills are used interchangeably with the term of "spatial abilities." In other literature, only the term of spatial skills [3, 4] or only the term of spatial abilities [5, 6] is used. Regardless of the term used, spatial skills or abilities are essential in many real-life situations. For example, a person traveling alone without a Global Positioning System (GPS) in an unfamiliar city must know what direction is East, West, South, or North in order to reach their destination. A person doing a puzzle game needs to identify correct shapes in order to connect all pieces successfully.

Spatial skills are especially important in learning science, technology, engineering, and mathematics (STEM) subjects [1–6]. In their recent widely-cited paper, Uttal et al. [3] conducted an extensive meta-analysis of studies on spatial training. They showed a positive correlation between spatial skills and academic achievements. They found that statistically, high academic achievements of a student when learning a STEM subject are positively correlated to his/her strong spatial skills. Wai, Lubinski and Benbow [6] analyzed the data drawn from a massive longitudinal study that tracked 400,000 U.S. high school students for more than 11 years. They found that spatial abilities assessed during adolescence are "a salient psychological attribute among those adolescents who subsequently go on to achieve advanced educational credentials and occupations in STEM." They suggested including spatial abilities in modern talent searches to "identify many adolescents with potential for STEM who are currently being missed."

Spatial skills are essential for learning and developing expertise in engineering, an essential "E" in STEM. For example, mechanical engineers create free-hand sketches and computer graphics of complex machines and components. Civil engineers create free-hand sketches and computer graphics of buildings, bridges, and structures. Manufacturing engineers make 3D prints of complex mechanical or electrical parts and components. Solid spatial skills or abilities are required in all these examples in order to complete the work tasks involved.

Studies have also been conducted to identify important factors affecting students' spatial skills, such as individual differences [7, 8] and gender [9].

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Mataix, León and Reinoso [7] recently conducted a study involving 750 college students from three majors: Civil Engineering, Chemical Engineering, and Industrial Electronic Engineering. A spatial test and a questionnaire survey were administered at the beginning and the end of the semester. They found that the factors affecting students' spatial skills included general intelligence, problem-solving ability, gender, construction games, and experience in technical drawing [7].

1.2 Interventions Developed to Improve Students' Spatial Skills

Training of students' spatial skills, nevertheless, have not yet received sufficient attention in STEM education because it is not a subject explicitly taught in the classroom [10–12]. To develop and improve students' spatial skills, various educational interventions have been developed, e.g., virtual reality [13, 14], augmented reality [15, 16] and digital sketching [17]. Herrera, Pérez, and Ordóñez [16] developed various virtual technologies including augmented reality. They reported that as the result of their interventions, the course grades (on a 0–100 point scale) of the experimental group were seven points higher than those of the control group.

Spatial training is often embedded in a computer-aided design (CAD) course [18–21] or other courses and workshops that last for either a semester or several weeks [22–24]. Novoa, Spencer, Hazlewood and Ortiz [21] provided a series of face-to-face, 2-hour training sessions for 34 freshman STEM students over six weeks in a semester. The results from their pre- and post-test showed that 85% of student participants improved test scores by nearly 18% on average. The change in test scores was found to be statistically significant.

Sorby, Casey, Veurink and Dulaney [24] developed a spatial intervention for freshman engineering students that consisted of weekly meetings over the semester in a 1-credit freshman orientation course. A total of 675 students participated in their study and were divided into an intervention group (n = 84) and a comparison group (n = 592). Their results showed that for students in the intervention group, the average score increased from 16 points on the pre-test to 22.5 points on the post-test. For students in the comparison group, there was only a 1.5-point increase from the pre-test score to the post-test score [24].

1.3 The Innovation and Contribution of the Present Study

In the previous effort to improve middle school students' spatial skills, Ha and Fang [25] developed the earliest version of an education technology called virtual and physical manipulatives (VPM). Unlike other technologies using either virtual manipulatives alone or physical manipulatives alone, VPM technology integrates virtual manipulatives with physical manipulatives in a concurrent and interactive manner, so that students can simultaneously use multiple senses to help the brain process a series of dynamic mental images while performing spatial tasks. This technology works by having a student hold a 3D concrete physical object (i.e., a physical manipulative) in their hands while sitting at a computer. An electrical sensor board, which contains an attitude heading reference system and an embedded microcontroller, is connected to the computer via a USB cable. Any physical movement of the object is captured by the sensor board, which sends orientation signals to the computer for real-time image processing.

The earliest version of VPM technology [25], which is referred to as the old VPM technology in this paper, has two major limitations. First, the manipulatives employed in spatial training were those with artificially created geometrical features with no real-world engineering applications. Fig. 1 shows two example manipulatives employed in spatial training in the previous work (the old VPM technology) [25]. Students often asked what those manipulatives were and what purpose they served. It is necessary to develop authentic manipulatives with real-world engineering applications to increase student interest and motivation to learn engineering.

Second, students could play with the manipulatives only on school computers, where the VPM computer program had been installed. This limited the chances for students to use the VPM computer program outside the classroom, e.g., at home.

The present study overcomes these two limitations of the old VPM technology and is significantly different from the previous work [25] in the following four regards. First, a new set of manipulatives that have real-world engineering applications has been developed in the present study to motivate and inspire student interest. By contrast, the manipulatives employed in the previous work [25] were those with artificially created geometrical features with no real-world engineering applications.

Second, a new computer program for VPM technology has been developed in the present study, enabling students to use VPM anywhere with the Internet, anytime, and at their own pace. By contrast, the computer program developed in the previous work [25] was outdated and did not have this functionality.

Third, student participants in the present study and the previous work [25] are completely different in terms of age and exposure to engineering. The present study focuses on engineering undergradu-

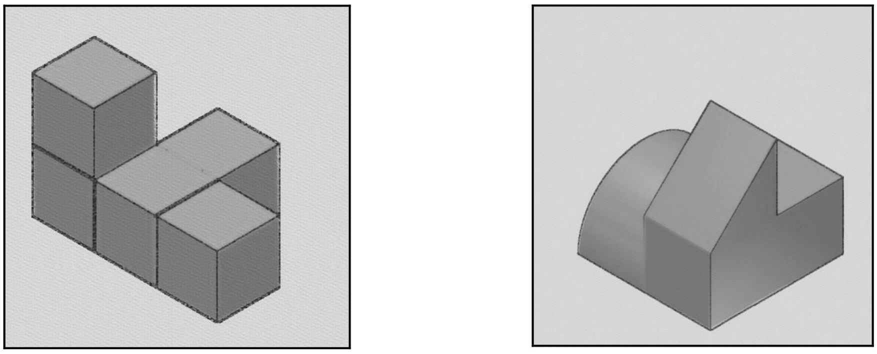


Fig. 1. Example manipulatives employed in spatial training in the previous work [25].

ates (adults) aged 21–25 years old. The previous work [25] focused on middle school 8th-grade students (adolescents) aged 15–16 years old.

Fourth, research design in the present study and the previous work [25] is completely different. The present study has involved two groups of student participants: an intervention group who was trained with the new version (rather than the earliest version) of VPM technology and a control group who was not trained with VPM technology. The previous work [25] only involved a single group of student participants who were trained with the old VPM technology. No control group was involved in the previous work. Therefore, in terms of research design, the present study is more rigorous than the previous work.

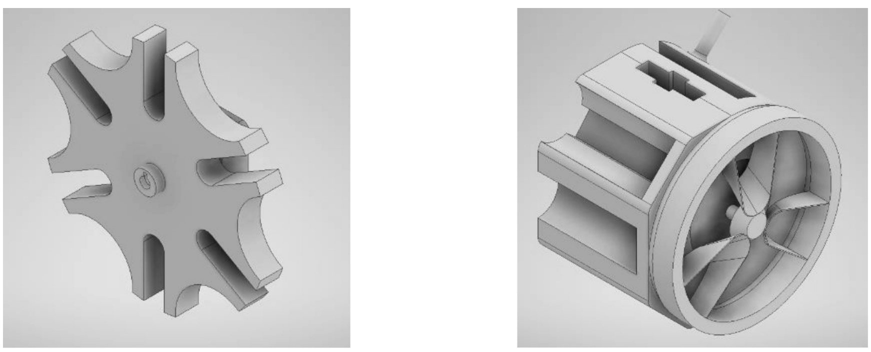
To differentiate from the old VPM technology developed in the previous work [25], the VPM technology developed in the present study is referred to as the new VPM technology. In the remaining sections of this paper, the development of the new VPM technology is described, including the development of ten manipulatives and a computer program for connecting virtual and physical manipulatives. Then, research questions, overall research design, student participants, as well as data collection and analysis are described. Next, the research results are presented and analyzed, followed by discussions and the description of the limitations of the present study. Conclusions are made at the end of the paper.

2. Development of the New VPM Technology

2.1 Design and Manufacture of Ten Manipulatives

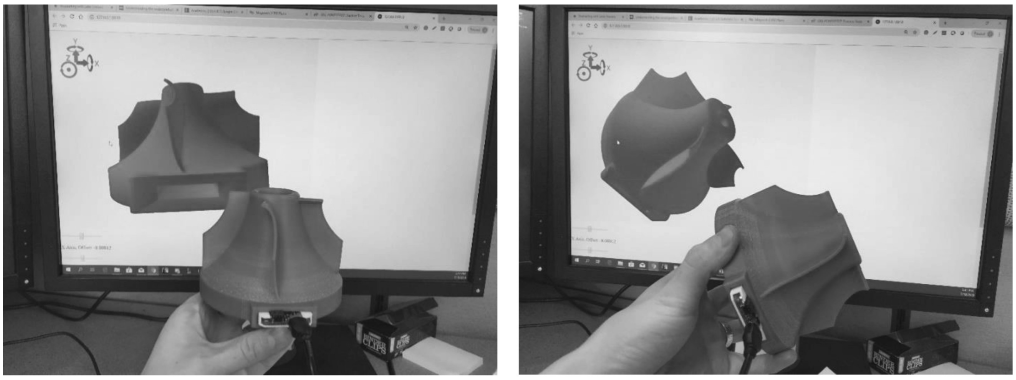
A total of ten manipulatives with real-world applications were designed via Autodesk Inventor Professional 2020 (a computer-aided design software package). The Autodesk Inventor-designed manipulatives were virtual manipulatives that students could see on a computer screen. Based on these virtual manipulatives, physical manipulatives were subsequently manufactured via 3D printing. Students then held and rotated physical manipulatives with their hands during spatial training. The ten virtual and physical manipulatives developed in the present study include Geneva wheel, spinner flasks, component grip, door lock, pulley, wheel bearing inside a hub, crankshaft, shaft arm valve, compressor wheel, and vacuum pump.

These manipulatives have a variety of levels of geometrical complexity, ranging from relatively simple and symmetric to complex and asymmetric. Fig. 2 shows two example manipulatives, including a Geneva wheel (Fig. 2a) with geometrically sym-



(a) (b)

Fig. 2. New manipulatives developed in the present study: example (a) Geneva wheel and example (b) vacuum pump.



(a) (b)

Fig. 3. The new VPM technology: a manipulative at (a) its initial orientation and (b) another orientation after rotation. The virtual manipulative shown on the computer screen rotates simultaneously with the physical manipulative held in the hand.

metric geometry and a vacuum pump (Fig. 2b) with complex geometry.

Each manipulative has real-world applications. For example, a Geneva wheel (Fig. 2a) is the rotating wheel of a gear mechanism called a Geneva drive, which translates a continuous rotation movement into intermittent rotary motion. Geneva drives have numerous engineering applications, e.g., in automated sampling devices, banknote counting machines, and film movie projectors. The Geneva wheel was selected as a manipulative for the new VPM technology due to its geometrically symmetric features. It requires low to medium cognitive effort for students to mentally rotate this manipulative. An additional advantage is that while students were trained with this manipulative, students could also understand how the mechanism works in a Geneva Drive in terms of fundamental science and engineering concepts like rotational motion, intermittent motion, angular speed, and angular acceleration.

A vacuum pump (Fig. 2b) removes the molecules of air and other gases from a sealed container or volume. It has numerous engineering applications, such as in the automotive and aerospace industries. The vacuum pump was selected as a manipulative for the new VPM technology due to its complex geometry. It requires medium to high cognitive effort for students to mentally rotate this manipulative. While students were trained with this manipulative, students could visualize the geometrical complexity of vacuum pumps, understand reasons, and develop an initial understanding of internal systems inside a vacuum pump.

2.2 Development of a Computer Program for Connecting Virtual and Physical Manipulatives

A computer software package called Processing (a new version with P5 Serial Control written for JavaScript) was employed to develop a computer program to enable the new VPM technology. This computer program communicated with a key hardware component to convert the motion of physical manipulatives in the real world to the motion of virtual manipulatives on a computer screen. The key hardware component was an Inertial Measurement Unit (IMU) board 9DoF (Degrees of Freedom) Razor IMU M0 manufactured by SparkFun Electronics. This key hardware component combines a SAMD21 microprocessor with an MPU-9250 9DoF sensor to create a reprogrammable IMU. The MPU-9250 9DoF sensor includes three 3-axis sensors to sense linear acceleration, angular rotation velocity and magnetic field vectors.

The IMU board was connected to a computer with a serial connection over USB with the baud rate set to 115,200 bits per second. The IMU board could also be connected using serial over Bluetooth with the use of a Li-Po cell and a Bluetooth adapter. The data sent by the IMU board with its default firmware and Euler angles toggled on was formatted as follows: Time stamp: milliseconds; Accelerometers X, Y, and Z: $m/s^2/9.8$; Gyroscopes X, Y, and Z: Micro Tesla; Euler angles X, Y, and Z: Degrees. The send rate was set to be 20 HZ in the new VPM technology.

As an example, Fig. 3 shows a physical manipulative and its corresponding virtual manipulative (compute image) developed in the present study. A student can rotate the physical manipulative in three directions around the x-, y-, and z-axes. When the student rotates the physical manipulative to observe it from different orientations, for example, 45 degrees clockwise or 180 degrees upside down, the student can observe how the image of the exact same virtual manipulative simultaneously rotates and changes its orientation on the computer screen.

3. Research Design and Data Collection

3.1 Research Questions and Overall Research Design

This paper focuses on the assessment of the new VPM technology. Therefore, the research questions of the present study are: Does the new virtual and physical manipulatives (VPM) technology enhance undergraduate engineering students' spatial skills? If yes, to what extent?

Quasi-experimental research design [26, 27] was adopted to answer the above research questions. Two groups of student participants were involved: an intervention group who was trained with the new VPM technology and a control group who was not trained with any VPM technology. Both groups completed a pre- and post-test using the same assessment instrument called the Revised Purdue Spatial Visualization Test: Visualization of Rotations (Revised PSVT:R) [28]. Section 3.3 (data collection) will describe some details of the revised PSVT:R instrument.

3.2 Student Participants

A total of 71 undergraduate students from the College of Engineering at Utah State University, a public research university in the Mountain West area of the U.S., were recruited to participate in the present study. Student participants were recruited through emails and classroom visits. Those who responded and showed interest in participating in the present study were contacted to find out if they could devote a sufficient amount of time to complete necessary tasks designed in the present study. All student participants signed on the Informed Consent form approved by the University's Institutional Review Board before they participated in the present study.

All 71 student participants were second-year undergraduates majoring in mechanical engineering, civil engineering, biological engineering, or other engineering fields such as aerospace and environmental engineering. The intervention group had 37 students. The control group had 34 students. Table 1 shows student demographics of each group. Among 71 student participants, 56 (79%) were males, and 15 (21%) were females. Engineering schools across the U.S. typically have 10–25% of female students in their engineering programs. Therefore, the percentage of female students involved in the present study was representative. In addition, the majority of student participants involved in the present study majored either in mechanical engineering (44 students or 62%) or in civil engineering (17 students or 24%).

3.3 Data Collection

Each of the 71 student participants completed a pre- and post-test using the same measurement instrument called the Revised Purdue Spatial Visualization Test: Visualization of Rotations (Revised PSVT:R) [28]. The instrument consists of 30 multiple-choice items corresponding to 13 symmetrical and 17 non-symmetrical 3D objects, and quantifies changes in spatial skills in student participants. The revised PSVT:R instrument corrected ten figure errors in the original PSVT:R instrument [29]. With an internal consistency reliability of 0.86, the revised PVST:R instrument is frequently cited as the strongest measurement of students' mental rotation skills and has been widely used in research involving undergraduate education [30, 31].

Student participants in the intervention group were trained with the new VPM technology over a five-week period in the semester. On average, two physical manipulatives were provided to each student per week. Student participants were provided access to the new VPM technology over the Internet, so they could run all manipulatives remotely on their own computers. To ensure students complete their training, each student participant was also provided a comprehensive workbook to use while they were trained with the new VPM technology. The workbook contains a set of multiple-choice questions corresponding to each of the ten manipulatives developed in the present study. While students were using the new VPM technology, they were required to answer those multi-choice questions, which enhanced the effectiveness of spatial training. Fig. 4 shows one representative example of worksheets included in the workbook.

To help student participants in the intervention group get started, we provided them initial guidance on how to use virtual and physical manipulatives. We also helped them solve computer hardware and software issues. After this initial

Table 1. Student demographics

Student groups	Number of students	Male	Female	Mechanical engineering major	Civil engineering major	Biological engineering major	Other engineering major
Intervention group	37	29	8	21	9	3	4
Control group	34	27	7	23	8	2	1
Two-group total	71	56	15	44	17	5	5

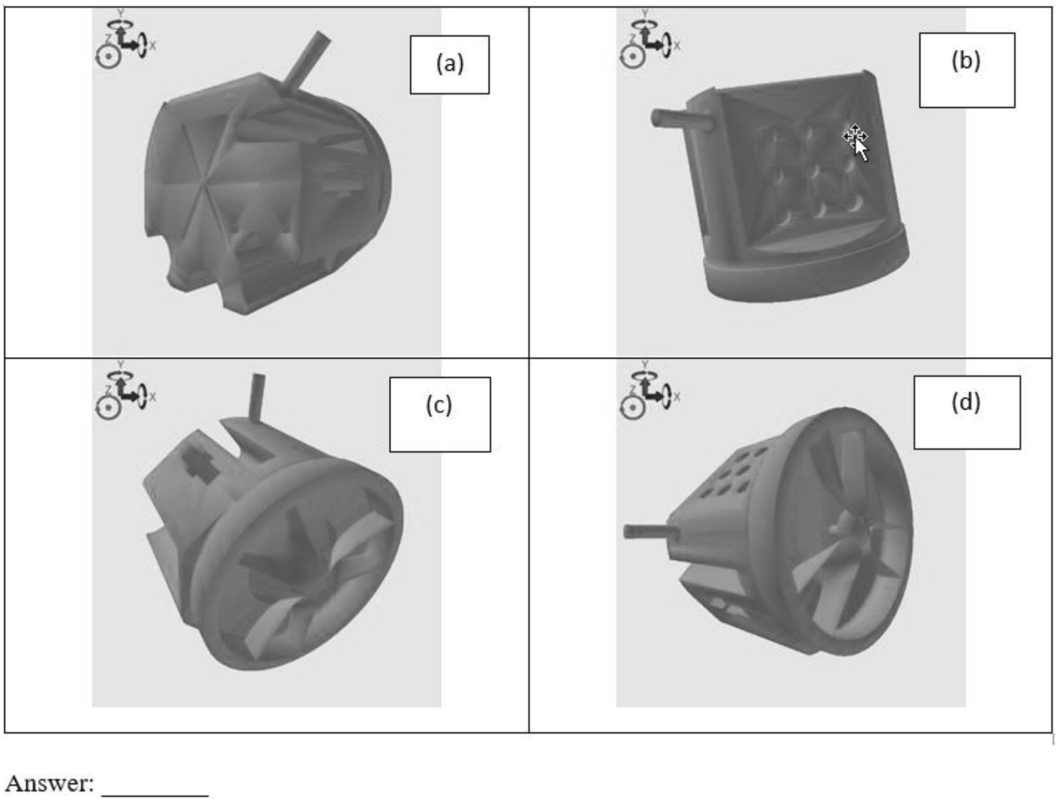


Fig. 4. An example worksheet developed for student participants to use during training with the new VPM technology.

assistance, student participants in the intervention group trained themselves with VPM technology over the five-week period in the semester. Each week, they were exposed to two manipulatives. The training with 10 manipulatives was completed at the end of the fifth week.

In addition to pre- and post-test scores, the cumulative grade point average (GPA) data of each student participant was also collected. The purpose was to determine if GPA was statistically significantly different between student participants in the intervention and control groups. If GPA were significantly different between the two groups, the two groups were not comparable.

4. Data Analysis and Results

4.1 Normality Tests

Normality tests on the data collected in the present study were first conducted to determine if parametric or non-parametric statistics should be employed. If the data had a normal distribution, parametric statistics would be employed. Otherwise, non-parametric statistics would be employed. Table 2 summarizes the results of normality tests for grade point average (GPA), pre-test scores, post-test scores, and normalized learning gains for the intervention and control groups. The normality tests conducted in the present study included both Kolmogorov-Smirnov tests and Shapiro-Wilk tests [27].

In Table 2, based on the pre- and post-test scores of each student participant, the normalized learning gain was calculated as [32]:

$$\text{Normalized learning gain (\%)} = \frac{\text{Posttest score (\%)} - \text{Pretest score (\%)}}{100\% - \text{Pretest score (\%)}}$$

In his widely-cited paper [32], Hake proposed the term of normalized learning gain in which both pre- and post-test scores are expressed in percentages, rather than absolute numbers. Although this term includes the word "normalized," it does not mean data distribution is always "normal." The "normalized" learning gain is a non-statistical term defined by Hake [32]. A "normal" distribution is a statistical term.

In Table 2, a p-value (i.e., the Sig. value in columns 4 and 7) less than 0.05 indicates a non-normal distribution of data. From Table 2, it can be seen clearly that GPA, pre- and post-test scores are not in a normal distribution for both intervention and control groups. The p-value for normalized learning gains is 0.2 (greater than 0.05) for the intervention group based on Kolmogorov-Smirnov tests, and 0.172 (greater than 0.05) for the control group based on Shapiro-Wilk tests. Further obser-

Table 2. Results of normality tests

Variables	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.[b]	Statistic	df	Sig.[b]
Grade point average (GPA)						
Intervention	0.151	37	0.034	0.904	37	0.004
Control	0.158	34	0.031	0.864	34	0.001
Pre-test scores						
Intervention	0.284	37	0.000	0.832	37	0.000
Control	0.154	34	0.039	0.888	34	0.002
Post-test scores						
Intervention	0.204	37	0.000	0.849	37	0.000
Control	0.158	34	0.031	0.919	34	0.015
Normalized learning gains (%)						
Intervention	0.111	37	0.200	0.939	37	0.044
Control	0.174	34	0.010	0.955	34	0.172

[a] Lilliefors significance correction.
[b] A p-value less than 0.05 indicates a non-normal distribution of data.

vations of normal Q-Q plots and analysis of homogeneity of variances [27] demonstrated that normalized learning gains do not have a normal distribution. Therefore, non-parametric statistical analysis was subsequently conducted for all data involved in the present study.

4.2 Descriptive Analysis

Table 3 summarizes the results of descriptive analysis, including mean, median, standard deviation, minimum, maximum, interquartile range, skewness, and kurtosis. Median and interquartile range are typically involved in non-parametric statistical analysis. Although mean and standard deviation are typically involved in parametric statistical analysis, they are still included in Table 3 because they have been most widely employed in the literature to describe and explain the results of a statistical analysis.

As can be seen from Table 3, all the values of mean, median, standard deviation, and interquartile range values of GPA are close for the intervention and control groups. For pre-test scores, the mean value is 23.62 for the intervention group and 1.5 points greater (25.12) for the control group. The median value is the same (26) for the two groups. For post-test scores, the mean value is nearly the same (25.97 and 26) for the two groups. However, the median value is 28 for the intervention group and 2 points less (26) for the control group.

For normalized learning gains, the mean value is 41.2% for the intervention group, which is 33% higher than that for the control group (8.2%). The median value is 50% for the intervention group, which is 41.6% higher than that for the control group (8.4%). The values of standard deviation and interquartile range for the control group are higher than those for the intervention group.

4.3 Correlation Analysis

Spearmen's correlation coefficients [27] were calcu-

Table 3. Results of descriptive analysis

Variables	Mean	Median	SD[a]	Min.	Max.	IQR[b]	Skewness	Kurtosis
Grade point average (GPA)								
Intervention	3.56	3.69	0.38	2.55	4.00	0.54	–0.94	0.16
Control	3.67	3.76	0.33	3.00	4.00	0.48	–0.88	–0.36
Pre-test scores								
Intervention	23.62	26	4.83	14	29	8.50	–0.77	–0.98
Control	25.15	26	3.29	18	29	4.30	–0.92	0.01
Post-test scores								
Intervention	25.97	28	4.08	14	30	5.50	–1.37	1.64
Control	26	26	2.87	18	30	3.00	–0.98	0.86
Normalized learning gains (%)								
Intervention	41.2	50	41.6	–66.7	100	51.1	–0.59	0.33
Control	8.2	8.4	53.1	–100	100	68.4	–0.34	–0.03

[a] SD stands for standard deviation.
[b] IQR stands for interquartile range.

Table 4. Spearmen's correlation coefficients between student groups (intervention or control) and other variables

	Grade point average (GPA)	Pre-test scores	Post-test scores	Normalized learning gains
Correlation coefficients	0.166	0.123	–0.082	–0.344*
Sig. (2-tailed)	0.167	0.308	0.494	0.003
N	71	71	71	71

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

Table 5. Results of independent-samples median tests (N = 71)

Variables	Median	Test statistic	Asymptotic sig.[a]
Grade point average (GPA)	3.71	0.347	0.556
Pre-test scores	26.00	0.024	0.877
Post-test scores	27.00	1.857	0.173
Normalized learning gains	33.30	7.839	0.005

[a] A p-value less than 0.05 indicates the statistically significant difference between the intervention and control groups.

Table 6. Results of independent-samples Mann-Whitney U tests (N = 71)

Variables	Mann-Whitney U	Standardized test statistic	Asymptotic sig.[a]
Grade point average (GPA)	749.500	1.389	0.165
Pre-test scores	717.500	1.027	0.304
Post-test scores	569.500	–0.690	0.490
Normalized learning gains	380.000	–2.881	0.004

[a] A p-value less than 0.05 indicates the statistically significant difference between the intervention and control groups.

lated for non-parametric statistical analysis in the present study. Table 4 shows how student groups (intervention or control) correlate to GPA, pre-test scores, post-test scores, and normalized learning gains.

Based on p-values (i.e., Sig. values listed in the third row of Table 4), student groups (intervention or control) are not statistically significantly correlated to GPA, pre- and post-test scores. However, student groups (intervention or control) are statistically significantly correlated to normalized learning gains (P = 0.003). Student participants in the intervention group were trained with the new VPM technology; whilst those in the control group were not trained with the new VPM technology. Therefore, it can be concluded that whether or not the new VPM technology was employed in spatial training is statistically significantly correlated to normalized learning gains.

4.4 Median Tests and Mann-Whitney U Tests

Median tests and Mann-Whitney U tests [27] for non-parametric statistical analysis were conducted to determine if there exists a statistically significant difference between the intervention and control groups in terms of GPA, pre-test scores, post-test scores, and normalized learning gains. Table 5 shows the results of independent-samples median tests. Table 6 shows the results of independent-samples Mann-Whitney U tests.

As can be seen from p-values in Tables 5 and 6 (i.e., asymptotic sig. values in the fourth column), there exists no statistically significant difference between the intervention and control groups in terms of GPA and pre-test scores. This implies that the intervention and control groups are comparable. There exists no statistically significant difference between the intervention and control groups in terms of post-test scores either.

However, Tables 5 and 6 show that there exists a statistically significant difference between the intervention and control groups in terms of normalized learning gains (P = 0.005 in median tests and P = 0.004 in Mann-Whitney U tests). Based on the data shown in Table 6, the effect size of the new VPM technology was further calculated as [33]:

$$\text{Effect size} = \frac{\text{Standardized test statistic score}}{\sqrt{\text{N}}}$$

where N is the number of student participants, which is 71 in the present study. The results of calculations show the effect size of the new VPM technology is 0.34, which represents a medium effect [33].

5. Discussions

The results described in the above section have demonstrated the effectiveness of the new VPM technology on improving students' spatial skills. One might ask how the new VPM technology compares to the old VPM technology in terms of students' learning gains. In the previous work [25], the old VPM technology was employed, and the results showed that the group-average normalized learning gain was 21.3%. In comparison, the new VPM technology developed in the present study led to a group-average normalized learning gain of 41.2%, nearly doubling the learning gain achieved by using the old VPM technology.

One might also ask how the new VPM technology compares to other existing technologies or methods that have been developed to improve students' spatial skills. To make the comparison reasonable, the same assessment instrument must be employed in the studies involved. This is because learning gains measured by different assessment instruments can be quite different [6]. The assessment instrument employed in the present study was the Revised Purdue Spatial Visualization Test: Visualization of Rotations (*Revised* PSVT:R) [28]. Extensive literature reviews using popular literature database, such as Scopus and Google Scholar, show that the vast majority of existing research involving the use of the Revised PSVT:R instrument have not provided relevant learning gain data because no post-tests were involved. The Revised PSVT:R instrument was employed to measure students' spatial skills and correlate them to student's academic performance or gender [28, 31, 34].

One exception is a recent study in which the Revised PSVT:R instrument was employed in two undergraduate engineering courses – computer-aided design (CAD) and computer-aided manufacturing (CAM) [35]. In these two courses, students rotated and visualized 2D and 3D objects from different orientations, which involved a significant amount of training and development of students' spatial visualization skills. A pre- and post-test using the Revised PSVT:R instrument was administered to measure students' spatial skills before and after these two courses in two semesters.

Student participants in the above study [35] were undergraduates in the Manufacturing and Mechanical Engineering Technology program at a public research university in the U.S. Table 1 of the paper [35] provided students' average pre- and post-test scores in the two courses:

- Students' average pre-test scores in semester 1: 26.1 (CAD) and 24.2 (CAM).
- Students' average post-test scores in semester 1: 25.2 (CAD) and 23.0 (CAM).
- Students' average pre-test scores in semester 2: 24.3 (CAD) and 24.7 (CAM).
- Students' average post-test scores in semester 2: 23.7 (CAD) and 24.5 (CAM).

Based on the above data, the class-average normalized learning gain in semester 1 was –48.7% for the CAD course and –45.8% for the CAM course. The learning gains were negative because the post-test score was less than the pre-test score. The class-average normalized learning gain in semester 2 was positive: 7% for the CAD course and 12.7% for the CAM course. These two percentage numbers, however, are significantly lower than the 42.1% of the normalized learning gain achieved by the new VPM technology developed in the present study. This comparison further demonstrates the effectiveness of the new VPM technology.

It is also worth mentioning that the students in the intervention group were trained with the new VPM technology for only five weeks between the pre- and post-test. This short time span (5-weeks) also demonstrates the effectiveness of the new VPM technology. According to relevant literature [3], spatial training with different techniques or methods involves a wide range of time frames from several weeks to several semesters. Few research studies have discussed how long is sufficient for spatial training to be effective. The results of the present study imply that as long as techniques for spatial training are powerful, the period of training can be reduced to just a few weeks.

The limitations of the present study need to be discussed. First, the sample size (n = 71 for two groups) is not large. Because each student participant in the intervention group must be committed to spending a significant amount of time over a five-week period, among their busy school schedules, in receiving spatial training with the new VPM technology, student recruitment turned out to be challenging. Some students did not participate in the present study because they could not make sufficient time commitment to receiving the training and completing pre- and post-tests.

Second, although the results of the present study have shown the effectiveness of the new VPM technology on enhancing undergraduate engineering students' spatial skills, it is unclear why the effectiveness of training (i.e., normalized learning gains) varies to different extents among different students. In the future work, each student participant's background and experience as well as the way in which he or she employs the new VPM technology during training will be examined. Qualitative research through interviews would also be helpful to explain why the effectiveness of training varies from one student to another.

6. Conclusions

In spite of the importance of spatial skills in learning and developing expertise in engineering, the training of students' spatial skills has not received sufficient attention. Except for computer graphic and computer-aided design courses, few engineering courses teach students how to develop spatial skills. This paper has described the new VPM technology that we recently developed to enhance undergraduate engineering students' spatial skills. Quasi-experimental research involving an intervention group (n = 37) and a control group (n = 34) has also been conducted. The following paragraphs summarize major research findings made in the present study:

1. The mean value of normalized learning gains is 41.2% for the intervention group, which is 33% higher than that for the control group (8.2%). The median value of normalized learning gains is 50% for the intervention group, which is 41.6% higher than that for the control group (8.4%).
2. Whether or not the new VPM technology was employed in spatial training is statistically significantly correlated to normalized learning gains ($P < 0.01$).
3. There exists no statistically significant difference between the intervention and control groups in terms of GPA, pre- and post-test scores.
4. A statistically significant difference exists between the intervention and control groups in terms of normalized learning gains ($P < 0.01$).
5. The new VPM technology has a medium effect size (0.34) on improving students' spatial skills.

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