Assessing Drawing Self-efficacy: A Validation Study Using Exploratory Factor Analysis (EFA) for the Drawing Self-efficacy Instrument (DSEI)

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Abstract

Drawing, as a skill, is closely tied to many creative fields and is a unique practice for every individual. Drawing has been shown to improve various skills that are critical in engineering education; cognitive and communicative abilities, such as visual communication, problem-solving skills, students' academic achievement, awareness of and attention to surrounding details, and sharpened analytical skills. While the base concept of drawing is a basic skill, the mastery of this skill requires extensive practice and it can often be significantly impacted by the self-efficacy of an individual. Self-efficacy is one's belief in his or her capacity to accomplish specific tasks. Self-efficacy is important when learning new skills because it aids in mastery, and also enables us to understand skill development. *Sketchtivity* is an intelligent tutoring system developed by Texas A&M University to facilitate the growth of basic sketching skills and track their performance. Sketching is a form of drawing that's focused on clear communication and generation of ideas. Skill development depends in part on students' self-efficacy associated with their sketching abilities. Rather than focusing only on sketching self-efficacy, we wanted to develop a more general tool for assessing drawing self-efficacy which could be applied in more domains than just our own and be useful for other researchers, educators, and technologists. A detailed validity study of the Drawing Self-Efficacy Instrument(DESI) is outlined in this paper.

Introduction

Drawing is a valuable skill that is interwoven with various fields and disciplines and unique for each individual. Cognitive and communicative skills such as visual communication, problem-solving skills, students' academic achievement, awareness of and attention to surrounding details, and sharpened analytical skills have been shown to improve with an increase in drawing skill [1, 2]. The physical act of drawing stimulates both sides of the brain and improves peripheral skills of writing, 3-D spatial recognition, critical thinking, and brainstorming [1–4]. However, as early as grades K-12, students with spatial abilities are overlooked by current gifted assessment programs [5]. Due to emphasis on mathematics and verbal reasoning in standardized testing, and less attention to assessment of spatial skills, these students may not be seen as likely to succeed according to current predictive models of academic success [6], despite its necessity in STEM fields and impact on other STEM subjects [7].

Studies by Sorby have consistently demonstrated that Spatial visualization skills are highly predictive of the success of an individual in engineering discipline. Students who are trained in sketching reports improved Spatial visualization skills [8]. Thus, learning sketching which is a form of drawing will contribute towards student's success in engineering. While the basic concept of drawing is relatively a common skill, mastery of the skill requires extensive focused practice and is significantly impacted by self-efficacy [9]. The development of drawing skill also depends in part on a person's self-efficacy associated with their drawing abilities [9]; higher self-efficacy leads to better skill development. Schunk found that ability feedback for early success during skill development promotes better achievement outcomes than that of ability feedback for later successes [9].

A mechanism to address the development of self-efficacy during drawing skill learning progression was implemented into the *Sketchtivity* software by Williford et al. [10–12]. *Sketchtivity* is an intelligent tutoring system to facilitate growth of basic sketching skills and track user performance. Sketching is a more loose, rapid form of drawing focused on clear communication and generation of ideas. *Sketchtivity* allows users to have regular and consistent feedback based on the user's performance. This early feedback mechanism can boost drawing self-efficacy during their journey towards mastery while tracking user progress over time.

One of the goals of *Sketchtivity* was to increase drawing self-efficacy of users along with drawing ability. Having a method to measure learner self-efficacy is intrinsic to understanding the process of drawing skill development.The absence of an instrument to assess drawing self-efficacy prevents us from evaluating the impact of the intelligent tutoring system on user's drawing self-efficacy. Hence, there is a need for an instrument that assesses drawing self-efficacy to make sure that students are mastering sketching and thereby gaining skills that contribute to their success in engineering. In addition, it is critical to gauge the drawing self-efficacy of individuals to compare traditional pedagogy with new teaching methods such as intelligent tutoring systems. Hence, the focus of this work was to define and develop a measurement tool to assess drawing self-efficacy. In order to expand the benefit of the assessment tool to more domains, other researchers, educators, and technologists, we developed a more inclusive drawing skill measurement tool rather than a tool to measure sketching self-efficacy of *Sketchtivity* users alone.

This paper describes the development, methodology, and performance of the Drawing Self-Efficacy Instrument (DSEI). During the development phase of our study, we hypothesized four factors to measure the drawing self-efficacy of the students that included:

- *Drawing specific things* (such as products, buildings, people, etc.)
- *Drawing to communicate ideas*
- *Drawing to solve problems*
- *Drawing to create*

We evaluated the DSEI's validity through analysis of the factor structure and functionality when assessing the drawing self-efficacy of high school engineering and art students.

Literature Review

Self-efficacy in education represents students' feelings of confidence in their ability to perform learning-related actions. It arises from the study of internal agency and its relationship to the environment, and is an indicator of a person's capabilities as measured by their self-beliefs [13]. The pursuit of learning goals is mediated by students' interests and the activities they perform to reach their goals [14]. Self-efficacy also interacts with outcome expectations, which are the anticipated consequences of performing a behavior, to reinforce student's perceptions of which actions are successful, and ultimately determine whether and how students will pursue goals [13, 14]. Self-efficacy also relies on student's self-regulatory abilities to evaluate goals, organize and focus their actions towards reaching them, and engage in stress-reducing and motivating strategies along the way [15]. Self-efficacy and outcome expectations are significantly influenced by past experiences, both positive and negative, that inform the likelihood of success and allow students to choose those behaviors which will help them achieve their goals.

There are many existing measures of self-efficacy in STEM and design education. The Science Self-Efficacy Scale (SESS) was developed by McBride et al. [16] to measure the confidence of arts and communication university students towards science literacy activities and applications. Sahendra linked mathematical self-efficacy with representation during mathematics problem-solving and found that high self-efficacy students were more likely to use strategies requiring multiple representations, and reference those representation when verifying their solutions [17]. In engineering, Lent et al. [14] measured self-efficacy of succeeding in engineering courses as (a) completing basic science and math requirements with good grades, (b) excelling in upcoming semesters and years, and (c) completing required upper-level courses for the degree. Carberry et al. [18] developed an instrument for measuring engineering design self-efficacy. It asked students to rate their confidence, motivation, anticipated success, and anxiety in performing engineering design activities such as identifying and researching a design need, developing design solutions, prototyping, and evaluating and testing the design. This scale was later applied by Hilton et al. [19] to measure improved design self-efficacy after a drawing intervention with a variety of approaches with freehand, 2D, and 3D drawing. However, there is a lack of instruments designed to assess drawing self-efficacy directly in STEM education as well as art and design.

Intelligent tutoring systems have many features which support the development of self-efficacy during drawing instruction. Mastery of drawing skill relies on self-efficacy, and students who repeatedly experience success when attempting drawing will have more positive outcome expectations and greater self-efficacy, which impacts future activity selection and practice [14]. Feedback is another important feature of intelligent tutors for promoting self-efficacy in drawing skill development. As large class sizes and online learning are becoming more prevalent, instructors are not able to provide individual feedback to all students, which has a negative effect on their self-esteem and learning experiences [12, 20–22]. Universally accessible feedback and personalized training features can support equity and student-centered learning by promoting self-efficacy where many students lack confidence and expertise. More accurate grading and personalized guidance during practice are possible with the use of intelligent drawing tools.

One such tool is *DrawMyPhoto*, a sketch-based tutoring system which generates portrait drawing tutorials through intelligently-generated steps and real-time feedback [23]. Williford et al.

collected participants' self-reported qualitative perceptions of confidence towards sketching after using the tool and found a greater improvement in self-perceptions of drawing ability in participants who had received full tutoring assistance than in participants who received no feedback and guidance, however no actual self-efficacy instrument was used. *PortraitSketch* from Xie et al. [24] similarly provides assistance in drawing portraits, but does so by tweaking user-generated strokes to conform better to the underlying portrait image. They found that the system did improve feelings of self-reported "ownership" of drawings and confidence in drawing ability, but again no self-efficacy instrument was used.

ZenSketch is another tool that takes more of a gamification approach to improve self-efficacy in basic line work. Students have reported improved motivation and self-efficacy from playing the game [25, 26], but the findings were largely qualitative.

This study examines self-efficacy with the tool *Sketchtivity*, a sketch-tutoring system that is focused on providing drawing feedback according to students' prior drawing experience and learning pace [10–12, 19, 27, 28]. *Sketchtivity* uses machine learning algorithms to support student learning through practice of freehand sketching in perspective.

While many educational drawing tools have been explored with great potential to improve drawing self-efficacy, few studies have tried to measure student's self-efficacy in their drawing ability in a truly comprehensive and quantitative manner that can be replicated in other studies.

Methods

A. Instrument Development

According to Fabrigar, the soundness of the items that are included in an instrument have an important role in utilizing the results obtained from Exploratory Factor Analysis (EFA) [29]. The Drawing Self Efficacy Instrument (DSEI) consists of 13 items that addresses four areas of Drawing efficacy. The DSEI was reviewed by an experienced designer and drawing instructor, Professor Wayne Li with more than 14 years of experience teaching drawing at Stanford and Georgia Tech. He confirmed that the questions were strong and promising for assessing confidence in drawing ability.

Fabrigar suggests that researchers must pay close attention while defining the respective domain of interest and in selecting the items to measure [29]. The four factors in our study included drawing specific things, drawing to communicate ideas, drawing to solve problems, and drawing to create. The results obtained from EFA are more accurate if each of the factors are represented by multiple items [29]. In order to represent the first factor, "drawing specific things", six items were designed including drawing products, buildings, person, vehicle, 2D, and 3D. In order to represent the second factor, "drawing to communicate ideas", three items were designed including drawing to communicate ideas, drawing to explain or teach a concept to others, and drawing to generate creative ideas for a project. In order to measure the third factor, "drawing to solve problems", two items were developed that included drawing to think through a truss problem, and drawing under pressure to come up with an idea. In order to measure the fourth factor, "drawing to create", two items were developed that included drawing to express myself and drawing from imagination. Fabrigar also recommends that a factor is represented by three to five items while designing studies for performing EFA [29]. The hypothesized third and fourth factors in our original hypothesis were represented by only two items each.

B. Participants

The participants in this study to test the performance of our Drawing Self-Efficacy Instrument (DSEI) were high school students enrolled in three different courses from three different high schools in Texas. The demographic distribution of students who participated in the surveys was not collected, however, we do have the data of the school districts through district aggregated "snapshots" each year [30]. Table 1 presents the demographics including race and economic disadvantage percentages of respective school districts.

Table 1: Demographics of the students in the three participating school districts [30].

District	# Students	White	Hispanic	African American	American Indian	Asian	Two or More Races	Economically Disadvantaged
Lovejoy	4,055	78.2	7.9	2.4	0.7	6.3	4.4	2.6
Giddings	1,916	32.2	55.7	9.1	0.1	0.6	2.3	69.5
Cedar Ridge	48,142	40.7	30.4	8.7	0.4	15.5	4.1	25.9

C. Data Collection

Data was collected in the Fall of 2017. *Sketchtivity* was deployed to three high school courses with teachers who were already teaching sketching as part of their curriculum. These teachers had participated in a summer research program with Texas A&M University. Two of the courses were introductory engineering courses, called Principles of Engineering and Introduction to Engineering Design while another was an art class called Fundamentals of Art. The instructors were encouraged to use the tool as little or as much as they wanted, to avoid drastically altering their curriculum.

As part of the pre-test, a 13 item drawing self-efficacy questionnaire was deployed to students. The response was collected in the form of scores ranging from 0–10, along with gender information of participants. Publicly available district data was used to gather demographic data on race. There were 222 students in total, of which, 70 were female and 152 were male; 2 students did not fill in the course or gender details.

Table 2: Participants in the study

District	Course	No of students in Sample	Male	Female
Lovejoy	Introduction to Engineering Design	16	13	3
Giddings	Fundamentals of Art	109	50	59
Cedar Ridge	Principles of Engineering	95	88	7

D. Data analysis

Factor analysis, a branch of multivariate analysis consisting of utilizing mathematical techniques to discover patterns among interrelated items and to discover the simplest way to interpret measured items, was employed in our study [31, 32]. Exploratory factor analysis (EFA) was used as a factor analysis technique to discover patterns by identifying the number of unobserved underlying factors and their underlying factor structure without making any prior assumptions about the relationship among measured items [29].

As a prerequisite for performing EFA analysis on the DSEI, we examined descriptive statistics, internal reliability, and bivariate correlation of the individual items [29]. All data analysis was performed using Excel, R, and Python. The behavior of the 13 individual items was assessed by examining the mean, standard deviation, skew and kurtosis. It was ensured that the responses of all the 13 items in the DSEI fell within the expected range of descriptive statistics. Skew and kurtosis coefficients were the employed asz measures of univariate normality. In order to assess the internal reliability, Cronbach's alpha provided us with a degree of consistency between individual items in the DSEI, and also helped us identify if any items should be removed [33]. An item that lowers the Cronbach's alpha of the DSEI might not potentially be measuring the main construct that we intend to measure [33]. The inter-item correlations were also examined prior to performing EFA. The linear bivariate correlation of all individual item pairs helped us to examine how well the items correlated with each other; items that are highly correlated with each other measure a single underlying construct [34]. Items with a correlation less than 0.30 may need to be removed as it might indicate a measurement error [34].

Further, in order to determine if the data were suitable for performing EFA, Bartlett's Test of Sphericity and the Kaiser-Meyer-Olkin Sampling Adequacy Test were performed. Bartlett's Test of Sphericity helps us to determine if the items are related to each other [35]. A value that is less than 0.05 indicates that the data is suitable for factor analysis. KMO value measures the proportion of variance in the items that are caused by underlying factors. KMO values greater than 0.8 indicates that data is suitable for EFA. A value less than 0.5 indicates that data is not suitable for EFA.

The 13 items are a measure of every factor that exists, and the loading pattern helps us to identify the factor and items that have the strongest relationship between each other. Factor loading values close to -1 or 1 indicates that the factor is strongly represented by the item. Factor loading values close to 0 indicates that the factor is weakly represented by the item. According to Kline, factor loading values of 0.30 or higher is considered to be strong for a study with 100 participants [36]. Best practices in using EFA analysis requires decision making in regards to factor extraction, number of factors to retain, and rotation method. To obtain the best result for normally distributed data, Maximum Likelihood was utilized as a factor extraction method. Scree Test [37] was utilized to find Eigenvalues greater than 1 for the purpose of finding the recommended factors to retain. Promax [38], an oblique rotation method that allows correlation between factors was used to get the accurate solution [29]. A systematic and detailed EFA was performed and three models with two factors, three factors, and four factors respectively were examined to find the best fitting model. The goodness of fit indices such as Chi-square, Tucker-Lewis Index (TLI) [39], root mean square of the residuals (RMSR), and the root mean square error of approximation (RMSEA) were utilized for examining and comparing the fitness of the three models [40].

Results

A. Descriptive Statistics

The descriptive statistics of the 13 items that were developed for the Drawing Self-Efficacy Instrument (DSEI) were calculated (see Table 3). The mean score of participant responses ranged from 4.36 to 6.96 on the zero to ten point Likert-type scale questionnaire. The standard deviation ranged from 2.43 to 2.86. The skew values were less than or equal to $|0.6|$ for all items except for an item, "Drawing a 2D Object" whose skew was -1.29. The kurtosis values ranged from -1.74 to 1.61.

Table 3: Univariate Summary Statistics(n=222).

Items	*M*	*SD*	Skew	Kurtosis
Drawing to communicate ideas to others	5.68	2.55	-0.27	-1.31
Drawing to express myself	5.49	2.79	0.03	-1.74
Drawing to generate creative ideas for a project	6.25	2.43	-0.25	-1.15
Drawing when I am under pressure to come up with an idea	5.09	2.76	-0.02	-0.75
Drawing to explain or teach a concept to others	5.58	2.64	-0.16	-1.22
Drawing a 2D object	6.96	2.67	-1.29	1.61
Drawing a 3D object	5.33	2.74	-0.39	0.20
Drawing a person	4.36	2.86	0.41	-0.59
Drawing a product	5.78	2.51	-0.26	-0.21
Drawing a vehicle	4.85	2.54	0.60	-0.57
Drawing a building	6.33	2.48	-0.34	-0.51
Drawing something from my imagination	6.00	2.70	-0.28	-1.14
Drawing to think through a problem	5.45	2.72	0.57	-0.75

B. Reliability

The reliability of the Drawing Self-Efficacy Instrument (DSEI) with 13 items as calculated by Cronbach's Alpha was 0.943. A value of Cronbach's Alpha between 0.7 and 0.9 is considered good, while a value above 0.9 is considered excellent [41]. As the reliability score was excellent, no items were removed.

C. Bivariate Correlations

The correlation between items ranged from 0.39 to 0.75, suggesting that the 13 items were well interconnected to each other (see Figure 1). As none of the bivariate correlations among items were less than 0.30, no item was removed prior to conducting EFA.

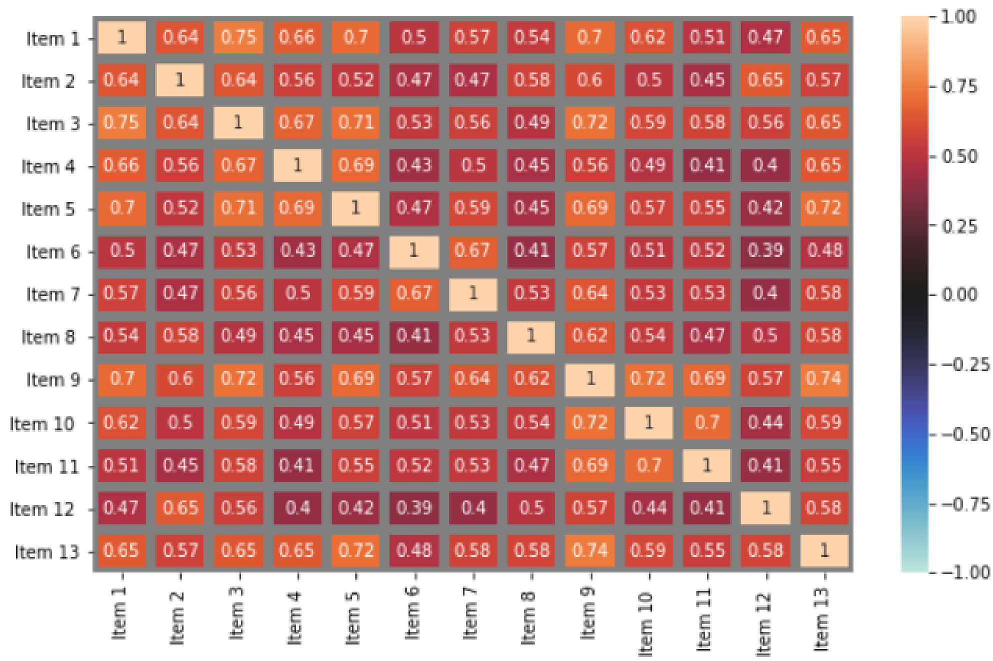

Figure 1: Correlation Matrix of Self Efficacy Instrument (DSEI)

D. Exploratory Factor Analysis

The dataset was subject to EFA with Maximum Likelihood Extraction method and Promax rotation. The KMO values for the 13 individual items were above 0.91, and the KMO measure was 0.9, indicating that the data were suitable for performing EFA. Bartlett's Test of Sphericity ($\chi^2(78)$ = 2092.49, p = 0) indicated that the items were highly related to each other. The Scree plot of the eigenvalues suggested a Two-factor structure for the model (see Figure 2).

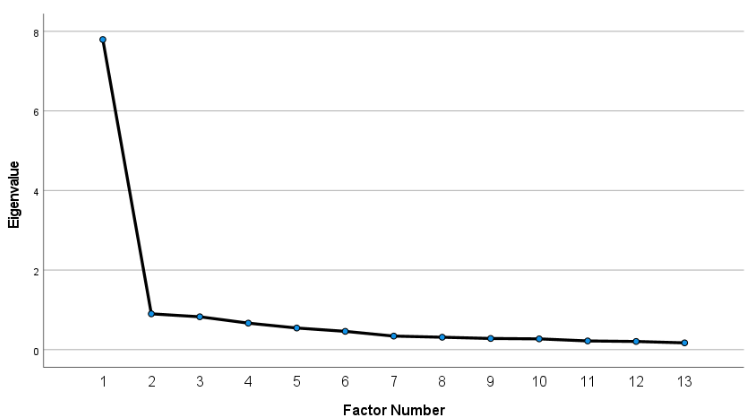

Figure 2: Scree Plot of Eigenvalues

Below is a table that describes the factor loadings of 13 items for a Two-Factor Model after rotation (see Table 4). Both factors were represented by six items. Item 12 ("Draw something from my imagination") cross-loaded onto both factors with slightly higher loading on second factor. For each variable, the amount of variance explained by the factor or communality (h2) ranged from 0.39 to 0.8. Hoffman's index of complexity (com) was very high for Item 12 (Drawing something from my imagination) indicating that it loaded onto both the factors. See Figure 3 for a visual representation of the Two-factor structure. The Sum of the Square loadings are 4.04, 3.88 for factor 1 and factor 2 respectively.

Table 4: Two-Factor Model Item Factor Loadings.

Items	F1	F2	h2	u2	com
Drawing to communicate ideas to others	**0.73**	0.14	0.71	0.29	1.1
Drawing to express myself	**0.56**	0.19	0.52	0.48	1.2
Drawing to generate creative ideas for a project	**0.70**	0.18	0.73	0.27	1.1
Drawing when I am under pressure to come up with an idea	**0.99**	-0.22	0.68	0.32	1.1
Drawing to explain or teach a concept to others	**0.72**	0.13	0.69	0.31	1.1
Drawing a 2D object	0.14	**0.54**	0.43	0.57	1.1
Drawing a 3D object	0.25	**0.50**	0.52	0.48	1.5
Drawing a person	0.20	**0.50**	0.45	0.55	1.3
Drawing a product	0.18	**0.75**	0.82	0.18	1.1
Drawing a vehicle	-0.01	**0.81**	0.66	0.34	1.0
Drawing a building	-0.17	**0.93**	0.64	0.36	1.1
Drawing something from my imagination	0.32	0.34	0.39	0.61	2.0
Drawing to think through a problem	**0.54**	0.32	0.68	0.32	1.6

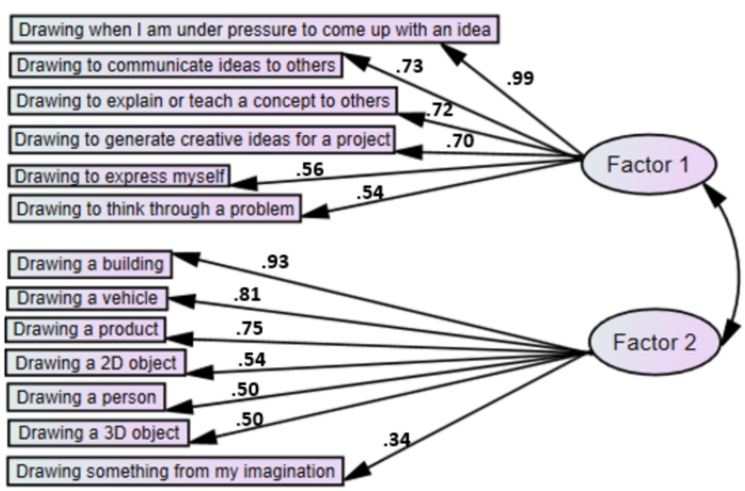

Figure 3: Two-Factor Structure

Below is a table that describes the factor loadings of 13 items for a Three-factor Model. The first and second factors consisted of five items each, and the third factor consisted of three items. For each variable, the amount of variance explained by the factor or communality (h2) ranged from 0.43 to 0.81. Hoffman's index of complexity (com) was highest for Items 8 and 13 ("Drawing a person" and "Drawing to think through a problem"). See Figure 4 for a visual representation of the Three-factor structure.The Sum of the Square loadings are 3.19, 3.29 and 2.00 for factor one, factor two, and factor three respectively.

Table 5: Three-Factor Model Item Factor Loadings.

Items	F1	F2	F3	h2	u2	com
Drawing to communicate ideas to others	**0.63**	0.11	0.15	0.70	0.30	1.2
Drawing to express myself	0.17	-0.14	**0.81**	0.72	0.28	1.1
Drawing to generate creative ideas for a project	**0.59**	0.14	0.19	0.73	0.27	1.3
Drawing when I am under pressure to come up with an idea	**0.93**	-0.19	0.05	0.68	0.32	1.1
Drawing to explain or teach a concept to others	**0.86**	0.21	-0.21	0.77	0.23	1.2
Drawing a 2D object	0.11	**0.51**	0.08	0.43	0.57	1.1
Drawing a 3D object	0.26	**0.50**	0.00	0.52	0.48	1.5
Drawing a person	-0.04	0.33	**0.47**	0.51	0.49	1.8
Drawing a product	0.14	**0.69**	0.13	0.81	0.19	1.2
Drawing a vehicle	0.00	**0.80**	0.02	0.66	0.34	1.0
Drawing a building	-0.11	**0.96**	-0.09	0.67	0.33	1.0
Drawing something from my imagination	-0.1	0.03	**0.82**	0.60	0.40	1.0
Drawing to think through a problem	**0.46**	0.27	0.16	0.68	0.32	1.9

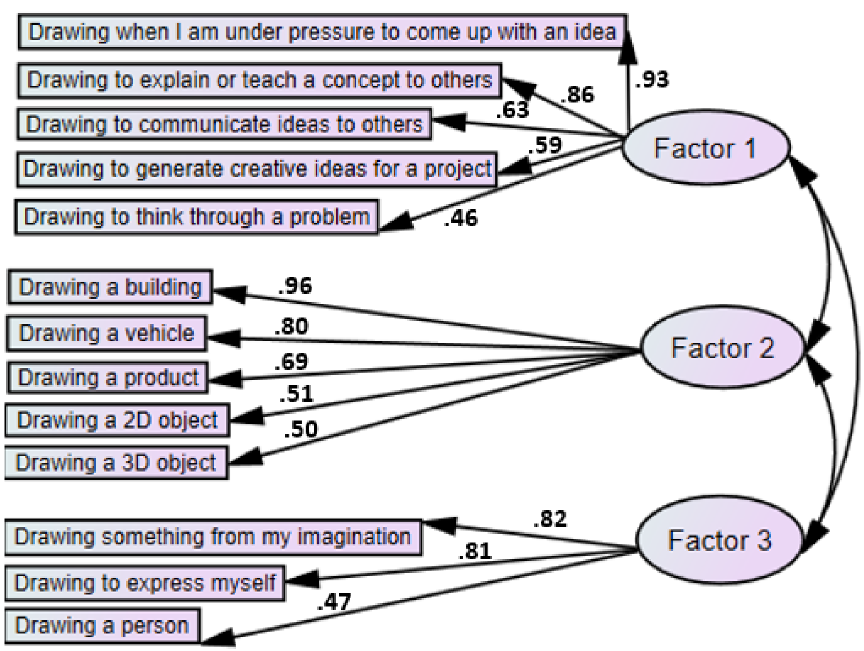

Figure 4: Three-Factor Structure

Below is a table that describes the factor loadings of 13 items for a Four-factor Model (see Table 6). Two items loaded onto Factor 1, three items loaded onto Factors 3 and 4 respectively, and five items loaded onto Factor 2. For each variable, the amount of variance explained by the factor or communality (h2) ranged from 0.51 to 1.00. Hoffman's index of complexity (com) was highest for Item 13 ("Drawing to think through a problem"). See Figure 5 for a visual representation of the Four-factor structure. The Sum of the Square loadings are 1.47, 3.15, 2.41, and 2.05 for factor one, factor two, factor three and factor four respectively.

Table 6: Four-Factor Model Item Factor Loadings.

Items	F1	F2	F3	F4	h2	u2	com
Drawing to communicate ideas to others	0.01	**0.64**	0.08	0.16	0.70	0.30	1.2
Drawing to express myself	-0.04	0.17	-0.14	**0.84**	0.72	0.28	1.2
Drawing to generate creative ideas for a project	-0.04	**0.61**	0.14	0.20	0.73	0.27	1.3
Drawing when I am under pressure to come up with an idea	0.02	**0.92**	-0.20	0.04	0.68	0.32	1.1
Drawing to explain or teach a concept to others	0.04	**0.88**	0.16	-0.23	0.77	0.23	1.2
Drawing a 2D object	**0.49**	0.02	0.19	0.08	0.51	0.49	1.4
Drawing a 3D object	**1.09**	0.05	-0.11	-0.08	1.00	0.01	1.0
Drawing a person	0.15	-0.05	0.19	**0.49**	0.51	0.49	1.5
Drawing a product	0.03	0.18	**0.61**	0.15	0.81	0.19	1.3
Drawing a vehicle	-0.06	0.04	**0.82**	0.02	0.69	0.31	1.0
Drawing a building	-0.01	-0.06	**0.95**	-0.09	0.69	0.31	1.0
Drawing something from my imagination	-0.05	-0.08	0.02	**0.86**	0.60	0.40	1.0
Drawing to think through a problem	0.02	**0.48**	0.22	0.17	0.68	0.32	1.7

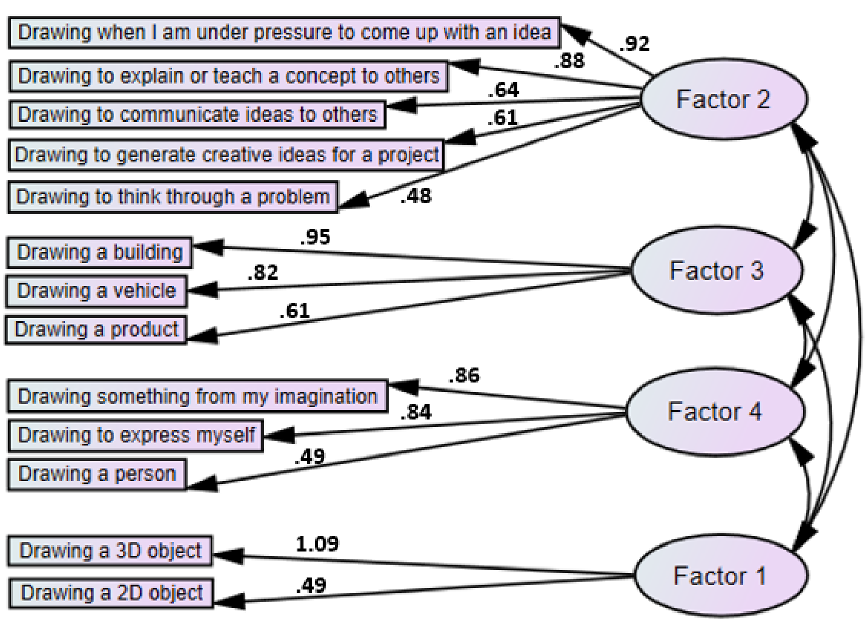

Figure 5: Four-Factor Structure

E. Fit Statistics

The fit indices consisting of Chi-Square, root mean square of the residuals (RMSR), Tucker-Lewis index (TLI) [39], root mean square error of approximation (RMSEA), and Bayesian information criterion (BIC) [42] were examined for the three models (See Table 7).

A Two-Factor model was suggested by the scree plot of eigenvalues (see Figure 2). Fit statistics included a high TLI value (0.9), but the high Chi square value (χ^2 = 188.87, p = 3.91E-17) indicated that the model is significantly different from the observed data (see Table 4). In addition, a high RMSEA value (0.107) suggests low parsimony of this model. Factor loadings were generally high overall for both factors ranging from 0.50 to 0.99. Only one item (Item 12, "Draw something from my imagination") had cross-loading. See Figure 3 for a detailed structure of items that grouped together.

The Three-factor model showed comparable performance with a high TLI (0.94), and a lower but still significant Chi square value (χ^2 = 118.48, p = 3.20E-9). The RMSEA value (0.09) was closer to an acceptable range, indicating better parsimony compared to a Two-Factor model (see Table 5). Factor loadings ranged from 0.46–0.96 overall, and all the items loaded significantly onto one factor. Each factor had atleast three items, with the strongest-loading item being Item 11 ("Drawing a building") in Factor 2 (0.96). See Figure 4 for a detailed structure of items that grouped together.

Our original hypothesis stated the possibility of a fourth factor and that led us to test a Four-factor model. This model had the lowest Chi square value, but was still significant (χ^2 = 74.74, p = 2.80E-5). Fit statistics included the highest TLI value (0.948) and lowest RMSEA (0.077) of all three models. Nearly half of the items had relatively low factor loadings (0.48–0.64). The first factor contained only two items, which is acceptable given the DSEI is relatively short. However, it is difficult to interpret the first factor, as Item 6 ("Drawing a 2D object") has a low loading of 0.49 and Item 7 ("Drawing a 3D object") has a very high loading of 1.09. These two drawing activities are similar, and yet seem to load oppositely onto the same factor. See Figure 5 for a detailed factor structure of items that grouped together.

Table 7: Fit Statistics of three models.

Model	χ^2	df	p-value	RMSR	TLI	RMSEA	BIC
2 Factor	188.87	53	3.91E-17	0.05	0.9	0.107	-97.48
3 Factor	118.48	42	3.20E-09	0.03	0.929	0.09	-108.43
4 Factor	74.74	32	2.80E-05	0.02	0.948	0.077	-98.14

Discussion

We conducted Exploratory Factor Analysis to examine the item correlations and factor structure of the Drawing Self-Efficacy Instrument (DSEI) in the context of high school art and engineering classes. The original hypothesis during the DSEI development phase suggested having four factors to measure the drawing self efficacy of the students. The four factors included drawing specific things, drawing to communicate ideas, drawing to solve problems, and drawing to create. With an aim to measure the first factor, "drawing specific things", six items were developed including drawing products, buildings, person, vehicle, 2D, and 3D. In order to measure the second factor, “drawing to communicate ideas”, three items were developed including drawing to communicate ideas, drawing to explain or teach a concept to others, and drawing to generate creative ideas for a project. In order to measure the third factor, “drawing to solve problems” two items were developed that included drawing to think through a truss problem, and drawing under pressure to come up with an idea. In order to measure the fourth factor, “drawing to create”, two items were developed that included drawing to express myself and drawing from imagination. A systematic and detailed exploratory factor analysis was performed to explore the advantages and disadvantages of having two factors, three factors, and also four factors. An EFA with two factors was conducted as Scree plot suggested having two factors. Since it was hypothesized to have four factors to measure drawing efficacy, we performed EFA to explore the possibility of having four factors. Due to difficulties to interpret two factor model and four factor model, we explored the possibility of having three factors.

A Three-factor model was found to be the best fit for our data, given fit statistics and model interpretability. While factor loadings were good for a Two-factor model, fit statistics suggested lower parsimony compared to other models, and it significantly differed from the observed data, with Item 12 having no clear factor loading. A Four-factor model was not as interpretable based on definitions of drawing activity, even though its overall fit was the best of the three models. Therefore, we concluded a Three-factor model is the most interpretable for the DSEI. The factors are:

- *Factor 1: Self-efficacy with respect to drawing practically to solve problems, communicating with others, and brainstorming ideas*
- *Factor 2: Self-efficacy with respect to drawing specific objects*
- *Factor 3: Self-efficacy with respect to drawing to create, expressing ideas, and using one’s imagination*

This model improves on the Two-factor model, where all drawing activity with a purpose is grouped into a single factor. The Two-factor model does not account for the varied difficulty among drawing tasks, which impacts a student’s self-efficacy. The Two-factor model groups Item 12 “Drawing something from my imagination” into the same factor as drawing 2D and 3D objects, buildings, vehicles, and products. Both the Three-factor and Four-factor models differentiate between drawing to communicate and drawing creatively as expected in our hypothesis. In our hypothesis, we had assumed that drawing 2D and 3D objects were separate skills compared to drawing specific objects such as buildings, vehicles, and products. However, the Three-factor model made the factor structure more interpretable than the Four-factor model, by grouping drawing 2D and 3D objects along with drawing objects such as buildings, vehicles, and products.

The Three-factor model connects the ideation techniques of drawing under pressure, drawing to generate ideas, and drawing to think through a problem with communication purposes for drawing. These include drawing to explain or teach a concept and drawing to communicate ideas. Drawing for ideation is typically used at the beginning of the engineering or industrial design process whether students are brainstorming potential design solutions. Drawing for communication is more common in the later stages where students are sharing their finished prototypes. Despite this, communication of ideas or teaching concepts to others are relevant in the beginning stages of design as well. Thus, it is feasible that all of items were found to belong together. Drawing is a powerful way to generate, develop, test and share ideas with others.

The Three-factor model also connects drawing a person with drawing to express and drawing something from imagination together. The Four-factor model also had the same pattern. However, the Two-factor model grouped drawing a person and drawing something from my imagination with 2D, 3D drawing and drawing objects. We found that drawing a person best fits with drawing something from imagination and drawing to express myself as supported by both Three-factor and Four-factor models. It should be noted that drawing a person requires a different skill set from the rest of the items listed.

Limitations

We recognize that non-random sampling was a limitation of this study, where student participants could not be randomly selected to complete the survey. Our sample had a gender imbalance of fewer females than males, and was limited by demographics collected at the school level rather than the classroom level. A limitation of the Three-factor model we chose is the variability of individual item loadings within factors. Although loadings were acceptably high for nearly all items, within each factor were differences of 0.1–0.2 between items, suggesting that some items may need revision. In addition, Item 8 ("Drawing a person") consistently had the lowest factor loadings across all three models. Further item-level psychometric testing should be used to evaluate the performance of each item in more detail beyond its overall factor.

Implications and Future Directions

This study investigated the performance of a new Drawing Self-Efficacy Instrument (DSEI) in context of high school art and engineering education as well as other domains. Our aim was to observe the DSEI's measurement of four hypothesized drawing constructs in these environments. With exploratory factor analysis, we found the Three-factor model to be the best fit with constructs of drawing objects, drawing to communicate ideas, and drawing creatively. This model has implications for drawing instruction, where assignments might include a mix of technical and creative learning objectives to foster self-efficacy. In addition, learning to draw can be contextualized within larger projects or challenges, such as engineering design, so that students may have practice on the communication aspects of drawing which may improve self-efficacy.

Continuing research on this DSEI will include modifying individual items based on further expert feedback. We also plan to survey wider, more diverse populations of learners beyond engineering and art classes, to look for differences in self-efficacy. Expanding the target educational level to postsecondary and professional learners would provide additional validity evidence for the use of this DSEI across many learning settings. Future directions may expand the DSEI more generally to any researchers interested in measuring drawing self-efficacy, whether using digital drawing tools or in traditional contexts such as art studios. Finally, the DSEI may be used for pre/post assessment to measure effects of drawing skill development using intelligent tutoring systems.

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