Cognitive style and field knowledge in complex design problem solving:

A comparative case study of design decision support systems

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BIOGRAPHICAL SKETCH

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Abstract

Cognitive differences in how people perceive and process information have been broadly studied in the fields of education and psychology. Previous findings show that comprehension is optimized when information presentation aligns with the cognitive abilities and preferences of an individual. On the other hand, the possession of field knowledge has also been studied to influence learning outcome and perception. This paper aims to understand the effects of individual's information processing styles and field knowledge on design decision-making, specifically focusing on designer learning and user experience. Two distinct decision support systems interfaces were developed to better examine the effect using a mixed model design. A total of 48 college students participated in the quantitative study and interacted with the two different interfaces of a satellite design system in a randomized order. Then a representative subset of data samples was selected for further qualitative analysis. Results show significant impacts of field knowledge and visual processing style on learning and user experience as well as behavioral differences between different user groups. Potential interaction effects with the design support system interface type and cognitive styles were also observed.

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1. Introduction

Advancing technologies allow more intelligent and powerful functionalities in decision support systems for complex problems. Decision support systems (DSS) are designed to facilitate the decision process by providing manipulable, current, timely information that is accurate, relevant, and complete (Power & Sharda, 2009). They allow better decision-making by expanding the human capacity to completely and accurately assess available information (Rogers, 1996). This expansion of information processing capacity is needed for tackling complex design problems that many industries are facing today.

Complex design problems often are large in scale and multidisciplinary; to tackle such problems, it is necessary to determine possible interactions among the subsystems and their parts (Todd & Benbasat, 1999). DSS's simulation and optimization abilities allow users to manipulate these subsystems and components to examine the interactions. With the need to process and present such complex information, the design of these DSS interfaces can be crucial to the success of their implementations.

As multidisciplinary approaches are increasingly valued in problem-solving, teams are becoming more diverse with people coming from different professional and academic backgrounds. To facilitate such collaboration, the DSS interfaces need to support a variety of user groups who may exhibit very different cognitive processes. Therefore, it is important to understand the factors that potentially influence human-DSS interaction experience and performance. In addition, such exploration can assist underrepresented or disadvantaged populations where decision support systems can be designed to be more inclusive and equitable.

The goal of this thesis paper is to identify operable design principles to improve user performance and experience for a variety of users through the exploration of the effects of individual cognitive style and field knowledge on user learning, performance outcome and experience during complex design problem solving with DSS.

Two studies were conducted to both quantitatively and qualitatively examine the effects of individual cognitive styles and field knowledge on the DSS usage outcome for complex design problem solving. Study 1 looks at the main effects and interactions of individual cognitive style, field knowledge, and DSS interface design on user performance and experience. Using a between-subject design the experiment was conducted with 48 subjects recruited from different fields. Study 2 zooms in on the design problem solving process and aims to identify behavioral differences between different user groups. The protocol analysis method was adopted to analyze the selected representative sample to supplement and better understand the findings of Study 1.

2. Literature Review

2.1. Cognitive Style

One of the most critical components in decision-making process is the human decision maker, thus it is important to consider the ways decision makers acquire information to make judgments such as individual cognitive styles (Benbasat, 1977). Cognitive style is often defined as consistencies in one's acquisition and processing of information, including the considerations of perception, thought, memory, imagery, and problem solving (Benbasat, 1977). Furthermore, Sternberg and Grigorenko (1997) defined cognitive style as people's typically preferred modes of processing information. The field of cognitive style gained its popularity starting in the early 1950's, and since then, different dimensions of cognitive styles emerged over the years, such as sharpener versus leveler (Sternberg & Grigorenko, 1997), field dependent versus field independent (Witkin, Moore, Goodenough, & Cox, 1975), holist versus serialist (Pask, 1976), and verbalizer versus visualizer (Sternberg & Grigorenko, 1997).

Around the 1980s and 1990s, many studies examined these dimensions to study the potential influence of cognitive styles on DSS user performance. Benbasat and Schroeder (1977) examined the interaction effect of cognitive styles, presence of a decision aid, and different forms of information presentation on decision performance assessed by a decision making game. Analysis showed an interaction effect between cognitive style and the presence of decision aid on the number of reports needed while making decisions. High analytic thinkers with the help of the decision aid used fewer reports during decision-making than their counterparts without decision aids, and vice versa for low analytic thinkers. Benbasat and Dexter (1982) further explored this relationship and found an overall better performance measured by profit gained among the high analytic thinkers. An interaction effect of cognitive style and the presence of decision aids on decision time was also revealed. High analytic thinkers with decision aids took more time than those without, whereas low analytic thinkers with decision aid took a similar amount of time as those without.

Different dimensions of cognitive styles have been examined. In a study focused on the interaction effect of cognitive style and graphical representation of problem elements on DSS user performance in terms of decision quality, higher field dependency was associated with longer decision time with no influence on percent error; similarly, higher need for cognition was also associated with longer decision time, but with a higher percentage error (Crossland, Herschel, Perkins, & Scudder, 2000). Davis and Elnicki (1984) also found an interaction effect between cognitive styles assessed by the Myers-Briggs Type Indicator (MBTI) and data format on decision quality where high sensing-feeling cognitive styles were associated with better performance with tabular data and high experiential-feeling scores were associated with better performance with graphical-raw data.

Using similar methods, Green and Hughes (1986) added the element of training type and analysis revealed that performance was optimized when heuristic managers received seminar training and when analytic managers received hands-on workshop training. Studies have also considered the effects of user characteristics and user experience. Ramamurthy, King, and Premkumar (1992) studied how user characteristics influenced DSS effectiveness in the context of user performance and satisfaction. Individuals with higher sensing and thinking scores outperformed individuals with higher intuitive and feeling scores in terms of performance and efficiency; they also responded with less perceived difficulty and displayed more favorable attitudes towards the DSS with reference to perceived usefulness and willingness to use. (Ramamurthy et al., 1992)

There had been concerns regarding the ability of cognitive style research in the field of DSS design to produce operable design guidelines. Huber (1983) argued that there were inadequate theories in cognitive styles, poor operationalization, and insufficient research designs, which contributed to stagnation in the field. Furthermore, reviews of existing studies showed that cognitive style explained very little of DSS user performance (Huber, 1983). However, new efforts were made to unify the field of cognitive style in the 1990's (Blazhenkova & Kozhevnikov, 2009). Sternberg and Grigorenko (1997) further stated that the study of cognitive styles does show promise in terms of predicting school and other kinds of performances. Moreover, new advances in the field also provide exciting opportunities for new research areas in the context of DSS design. In this paper, we will be focusing on two dimensions of cognitive styles that had recent developments in theory and instrumentation: the rational-experiential cognitive style, and the object-spatial visualization style.

Rational and Experimental Cognitive Style

The cognitive-experiential self-theory describes two parallel and interacting modes of information processing, the rational cognitive style and the experiential cognitive style (Epstein, 1994). In this theory, the rational cognitive system is described as analytic and logical whereas the experiential system is attributed to being holistic and affective. Thus, individuals with high rational cognitive styles are characterized by the ability and reliance on thinking in a logical and analytic manner; individuals with high experiential cognitive styles have the ability and preference to rely on one's intuition and feelings in making decisions (Shiloh, Salton, & Sharabi, 1990). These two dimensions were chosen to build upon the existing literature connecting cognitive style to DSS usage, however, by taking on a slightly different theoretical perspective by using the rational-experiential cognitive styles.

Object and Spatial Visualization Style

Object and Spatial Visualization Style Studies had supported the existence of a visualizer-verbalizer dimension of cognitive style where visualizers primarily rely on imagery when performing cognitive tasks and verbalizers primarily rely on verbal-analytical strategies. Within the visualizer cognitive style, newer findings suggested two qualitatively different types of visualizers, object versus spatial visualization (Kozhevnikov, Kosslyn, & Shephard, 2005). They are related but distinct dimensions (Höffler, Koć-Januchta, & Leutner, 2017). Object visualization refers to processing visual information in terms of physical appearances like shape, color, and texture; spatial visualization refers to processing visual information in terms of spatial relationships such as location, movement, transformation and other spatial attributes (Blajenkova, Kozhevnikov, & Motes, 2006). In addition, object visualizers have a tendency to encode images globally as a single perceptual unit, which they process holistically, whereas spatial visualizers have a tendency to encode and process images analytically, in sequence of components, and use spatial relations to arrange and analyze them (Kozhevnikov et al., 2005).

A study has examined the interaction of cognitive style and information presentation format on comprehension specifically considering the object-spatial visualization styles in addition to the visualizer-verbalizer dimension of cognitive style (Thomas & Mckay, 2010). The information was distributed in three different forms: text only (verbal); text + picture (object visual); and text + schematic diagram (spatial visual). Results showed an optimization of comprehension when the information presentation matched with the cognitive style of the individual. In this paper, the author wishes to apply this finding in the context of DSS interface design to explore its implications on design problem-solving performance and user experience.

2.2. Field Knowledge

Field knowledge, also known as domain knowledge, refers to the knowledge related to the subject matter being examined and it is a key component in decision-making (Devine & Kozlowski, 1995). Many studies have examined the effect of field knowledge on design and decision performance. Yu, Honda, Sharqawy, and Yang (2016) examine this relationship in the context of designing complex desalination systems. They found that designers with more domain knowledge had higher efficiency but not necessarily higher performance. Another study investigated the effect of field knowledge on the number and quality of ideas generated in a brainstorming session. The results showed a higher number of ideas generated by individuals who were primed with prior knowledge in the subject matter, and they generally produced higher quality ideas as well (Rietzschel, Nijstad, & Stroebe, 2007). Devine and Kozlowski (Devine & Kozlowski, 1995) looked at possible interactions between field knowledge and task structure on information acquisition and decision accuracy, and observed that individuals with high field knowledge only performed better than individuals with low field knowledge in the condition with well-structured tasks.

In regards to the effect of field knowledge on learning outcomes, studies have examined this relationship in the context of hypermedia learning. Studies have reported superior performance in navigation among individuals who exhibit field knowledge (Florance & Marchionini, 1995; Patel, Gibson, Ratner, Besson, & Holcomb, 1998) and more disorientation in hypermedia systems among those who have little to no field knowledge (McDonald & Stevenson, 1998). Furthermore, field knowledge experts were also found to show more positive perceptions of their learning processes (Chen, 2002; Ghinea & Chen, 2003a). A study on field knowledge for multimedia-learning environments observed that design principles that assisted low field knowledge learners did not benefit or may even hinder high field knowledge learners (Mayer, 2002). Researchers (Mitchell, Chen, & Macredie, 2005) also found that individuals with lower field knowledge benefitted more from tutorials and examples than those with higher domain knowledge.

These findings illustrate the important role field knowledge plays in complex design problem solving, decision making and learning processes. Thus, it is an important variable to be incorporated into the studies to further explore its effects on DSS interactions in the context of complex design problem solving. Specifically, field knowledge will be defined as understanding of the context of the materials in the following studies, and not necessarily design expertise.

2.3. User Performance and Design Decision Support System

User performance has always been a key DSS outcome of interest. In the context of DSS usage, user performance can be measured in different ways. Sharda, Barr, and McDonnell (1988) measured DSS performance with decision efficiency and effectiveness. Another study defined DSS outcome as problem identification and problem prioritization (Santos & Bariff, 1988). In the context of this paper, DSS performance was measured by learning outcomes, because the ultimate goal for the designers in the study is to better understand the design problem and how to manipulate different parameters to achieve better outcomes with a DSS. Specifically, learning outcomes consisted of evaluations of comprehension and application of the information gained while interacting with the assigned DSS.

2.4. User Experience and Design Decision Support System

User experience is defined by ISO 9241-110:2010 (clause 2.15) as “a person’s perceptions and responses that result from the use and/or anticipated use of a product, system or service” or “a momentary, primarily evaluative feeling while interacting with a product or service” (Hassenzahl, 2008). In the context of information systems, researchers have found that higher user satisfaction with the system was associated with higher user performance and usage (Gelderman, 1998; Hou, 2012). Thus user experience is an important variable to consider in the study, as it is also a major part of system performance outcomes. Zinkhan, Joachimsthaler, and Kinnear (1987) operationalized DSS user experience with satisfaction with decision and satisfaction with the performance of the system. Ramamurthy, King, and Premkumar (1992) measured DSS user experience with established user information system satisfaction scales. In this paper, user experience refers to the subjective perception of the interactions with the DSS for design problem solving processes in terms of perceived performance, affect, and sensation. It will also be measured with established user experience scales that will be introduced in a later section.

3. Study 1: Effects of Cognitive Style and Field Knowledge

3.1. Interactive Feature Extraction for Engineering Design System

The Interactive Feature Extraction for Engineering Design system (iFEED) was the design decision support system (DDSS) used in the experiment (Bang & Selva, 2016). It addresses a real-world system architecture problem with a goal to design a constellation of satellites to provide operational observation of the Earth's climate. In the context of the design problem, satellites are being launched into 5 orbits around the Earth and each satellite can carry up to 12 instruments. The main objective of this task was to optimize the design of this constellation consisting of up to 5 satellites to maximize the scientific benefit and minimize the lifecycle cost.

The iFEED interface provided two main capabilities: to inspect individual designs and to run data mining algorithms to extract common features shared by a selected group of designs. Design inspections were done in the Objective Space, which consists of an interactive scatter plot of satellite constellation designs and a window that displays the configuration of the selected designs (Figure 1). The user could hover over any data point on the scatter plot and the window below would live update information on the data point highlighted. We consider this display as a literal representation of the data where a design's scientific benefit and cost are directly indicated on the plot and the literal configurations of each satellite are displayed.

Additionally, a Feature Space is used to extract or identify feature information shared by a selected group of designs using data mining (Figure 2). It also includes an interactive scatter plot with each data point representing a shared feature. The plot has two axes of coverage and specificity where coverage expresses how the fraction of designs in the desired region share this feature whereas specificity expresses how the fraction of designs outside of the region exhibit this feature. The feature details are displayed in a logic tree diagram on the right. We characterize this as an abstract representation of the data as it is showing information on a more conceptual level.

Table 1. Objective and Feature Space comparison

Objective Space	Literal and graphical display of satellite system configuration or design
Feature Space	Abstract tree diagram representation of features shared by a group of satellite system designs

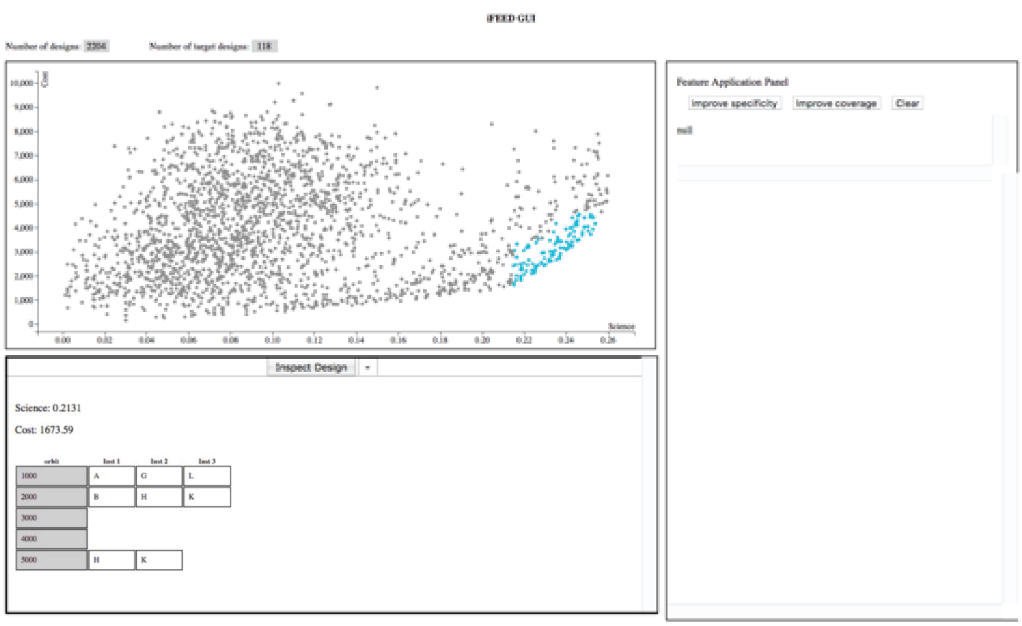

Figure 1. Objective (literal) Space of DDSS interface

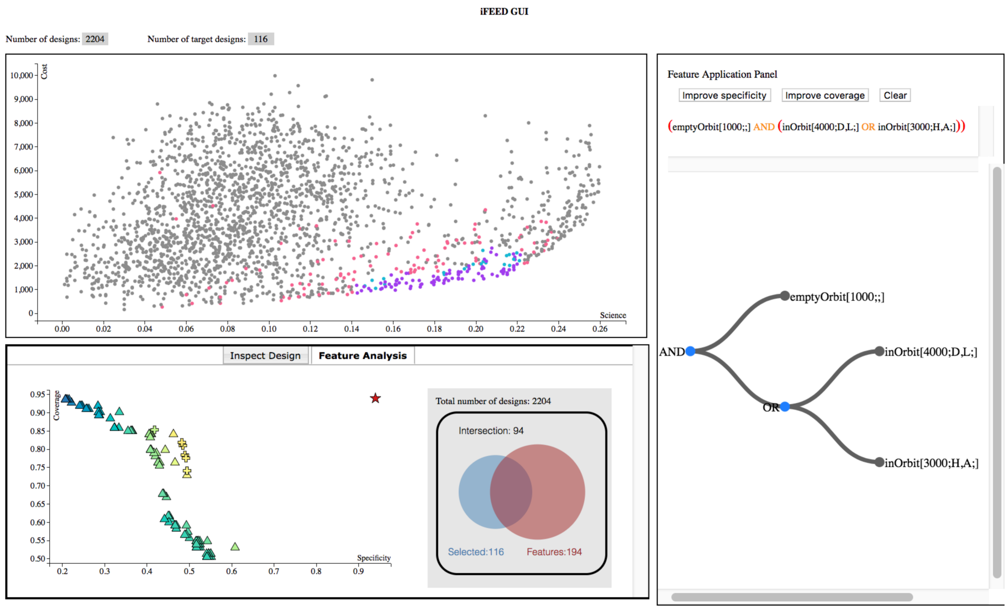

Figure 2. Feature (abstract) Space of DDSS interface

3.2. Participants

Undergraduate and graduate students enrolled in Cornell University were recruited by online and in class advertisements with participation incentives with either a 15 dollars Amazon gift card or extra credit. A total of 48 students, of which 20 (41%) were females, participated in the study. Thirty-four (70%) students were STEM majors: Science, Technology, Engineering, and Mathematics. Table 2 summarizes the sample demographics. None of the students had any prior interaction with the iFEED interface.

Table 2. Participant demographics

Characteristics		*N*
Major field	STEM	34
	NonSTEM	14
Year	Sophomore	7
	Junior	4
	Senior	5
	Graduate	28
Gender	Male	28
	Female	20
Ethnicity	Caucasian	21
	Asian	24
	Hispanic	2
	Others	1
Total (*N*)		48

3.3. Variables and Measures

An online survey using the Qualtrics system was sent to the participants prior to the study to gather demographic information such as gender, ethnicity, major field and school year. Field knowledge was determined by whether the student was in STEM majors or not as the context of the design task was heavily rooted in the field of engineering and mathematics. Different cognitive style scales were also included. The Object-Spatial Imagery Questionnaire (OSIQ) was used to measure individual visualization styles. The questionnaire consists of 40 Likert items that allowed participants to rate their level of agreement for each statement on a 5-point scale. In terms of internal consistency, the questionnaire has a Cronbach alpha of .79 for spatial measures and .83 for object measures. The questionnaire was also tested against established measures with acceptable convergent validity coefficient ranges (Blajenkova et al., 2006b). In terms of rational-experiential cognitive styles, the Rational-Experiential Inventory (REI) (Pacini & Epstein, 1999) was used and it has been tested to have satisfactory validity and reliability (Björklund & Bäckström, 2008).

A post-experiment questionnaire was used to assess learning and user experience from the given tasks with DDSS, which are the dependent variables of the study. Learning was evaluated by a quiz containing 25 items asking if specific satellite constellation designs would reside in the target region studied during the experiment. Then the User Experience Questionnaire (UEQ) (Ramamurthy et al., 1992) was administered to measure user experience. The UEQ has 26 sets of opposing adjectives and the participants would rate their experience on a 7-point scale within each of the 26 dimensions.

Table 3. Indpendent Variables

Variable		Levels	Measurement	Design
Cognitive Style	Object - Spatial Visualization Style	1. Object 2. Spatial	Object - Spatial Imagery Questionnaire (OSIQ)(Blajenkova, Kozhevnikov, & Motes, 2006)	Between Subject
	Rational - Experiential Cognitive Style	1. Rational 2. Experiential	Rational-Experiential Inventory (REI) (Pacini & Epstein, 1999)	Between Subject
Field Knowledge		1. STEM 2. NonSTEM	Self Report	Between Subject
DDSS Interface Design		1. Literal 2. Abstract	n.a.	Within Subject

Table 4. Dependent Variables

Variable	Measurement
User Performance	Post-task Quiz
User Experience	User Experience Questionnaire (UEQ) (Ramamurthy et al., 1992)

3.4. Procedures

The study followed a mixed model design with three independent and two dependent variables. The independent variables include cognitive styles, field knowledge, and DDSS interface variations. Cognitive style and field knowledge were between-subject variables whereas the DDSS interface variable was a within-subject variable. The dependent variables include learning and experience.

First, the pre-experiment online survey was sent via email to all participants after they have signed up for individual experiment time-slots online. They were instructed to complete the survey before their scheduled experiment times. Upon arrival to the lab, the participant was asked to sign a consent form and was directed to the computer station. They were first walked through an interactive tutorial regarding the iFEED system and the objectives of their tasks were given at the end. Then the participants interacted with one of the two DDSS interfaces (Object Space vs. Feature Space) at a randomized order for 10 min and the post-experiment questionnaire was administered. Then, the second interface was introduced and the same procedures were repeated.

3.5. Hypotheses

To explore the effect of individual cognitive style and field knowledge on user performance and experience during complex design problem solving with iFEED system, we built upon previous literature and 3 main hypotheses were generated:

- H1: Prior field knowledge will significantly influence iFEED usage outcomes.
    - H1a: Prior field knowledge will significantly influence learning outcomes such that higher prior knowledge will be associated with better learning outcomes. (Field Knowledge → Learning)
    - H1b: Prior field knowledge will significantly influence user experience outcomes such that higher prior knowledge will be associated with better user experience outcomes. (Field Knowledge → User Exp)
    - H1c: The system interface design will act as a moderator such that the effect of prior knowledge on learning and user experience outcomes will depend on the interface design. (Field Knowledge → Learning & User exp | DDSS)
- H2: Rational-experiential cognitive style will significantly influence iFEED usage outcomes.
    - H2a: Rational-experiential cognitive style will significantly influence learning outcomes such that highly rational designers will have better learning outcomes than highly experiential designers. (Rat. Exp. → Learning)
    - H2b: Rational-experiential cognitive style will significantly influence user experience outcomes such that highly rational designers will have better user experience outcomes than highly experiential designers. (Rat. Exp. → User Exp)

- H2c: Prior field knowledge will act as a moderator such that the effect of rational-experiential cognitive style on learning and user experience outcomes will depend on prior field knowledge. (Rat. Exp. → Learning & User Exp | Field Knowledge)
- H2d: The system interface design will act as a moderator such that the effect of rational-experiential cognitive style on learning and user experience outcomes will depend on the interface design. (Rat. Exp. → Learning & User Exp | DDSS)
    - H2d1: Highly rational designers will have more positive learning outcomes and user experience when information is presented in an abstract manner in the Feature Space.
    - H2d2: Highly experiential designers will have better learning outcomes and higher ratings of user experience when information is presented in a literal manner in the Objective Space.
- H2e: There will be a three way interaction affect between rational-experiential cognitive style x prior field knowledge x system interface design, such that the effect of rational-experiential cognitive style on learning and user experience outcomes will depend on both the interface design and prior field knowledge. (Rat. Exp. → Learning & User Exp | Field Knowledge, DDSS)

- H3: Object-spatial visualization style will significantly influence iFEED usage outcomes.
    - H3a: Object-spatial visualization style will significantly influence learning outcomes such that designers with high spatial visualization style will be

associated with better learning outcomes than designers with high object visualization style. (Obj. Spa. → Learning)

- H3b: Object-spatial visualization style will significantly influence user experience outcomes such that designers with high spatial visualization style will be associated with higher user experience outcomes than designers with high object visualization style. (Obj. Spa. → User Exp)
- H3c: Prior knowledge will act as a moderator such that the effect of object-spatial visualization style on learning and user experience outcomes will depend on prior knowledge. (Obj. Spa. → Learning & User Exp | Field Knowledge)
- H3d: The system interface design will act as a moderator such that the effect of object-spatial visualization style on learning and user experience outcomes will depend on the interface design. (Obj. Spa. → Learning & User Exp | DDSS)
    - H3d1: Designers with high spatial visualization style will have more positive learning outcomes and user experience when information is presented in an abstract manner in the Feature Space.
    - H3d2: Designers with high object visualization style will have better learning outcomes and higher ratings of user experience when information is presented in a literal manner in the Objective Space.
- H3e: There will be a three way interaction affect between object-spatial visualization style x prior field knowledge x system interface design, such that the effect of object-spatial visualization style on learning and user experience

outcomes will depend on both the interface design and prior field knowledge. (Obj. Spa. → Learning & User Exp | Field Knowledge, DDSS)

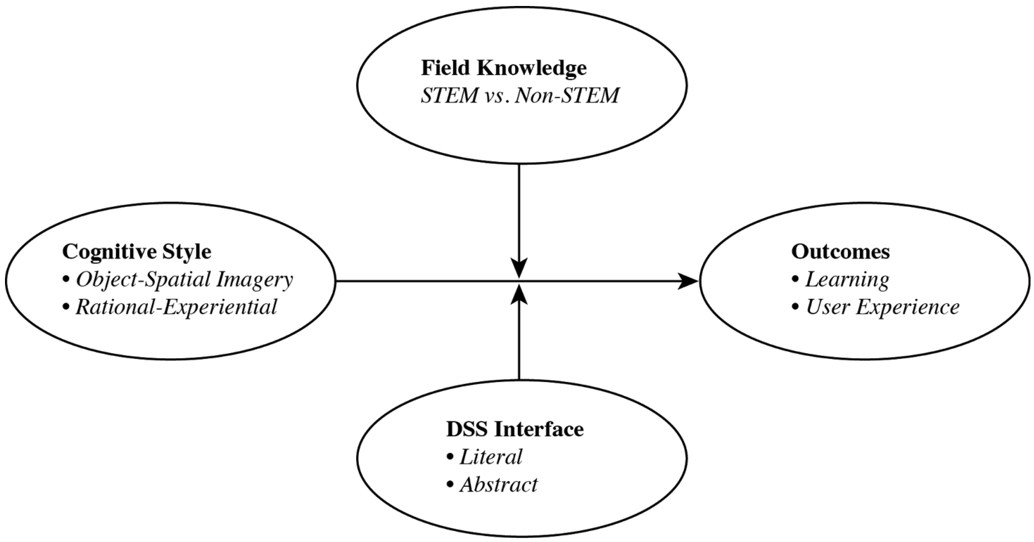

Figure 3. Research concept diagram

3.6. Results

A series of mixed model analyses were performed to examine the effects of cognitive styles and field knowledge on user experience and user learning using two types of DDSS interfaces. A mixed model was used because the experiment included both within-subject (Objective vs. Feature Space) and between-subject (STEM vs. non-STEM) independent variables; this would allow us to control for the random effects from individual characteristics.

Table 5. Correlation of study variables

DDSS	Measures	Outcomes		Cognitive styles			
		1. Learn	2. UEQ	3. Object	4. Spatial	5. Rational	6. Exp
Objective Space	1. Learning	-					
	2. User exp (UEQ)	.28	-				
	3. Object I. style	-.16	-.00	-			
	4. Spatial I. style	.10	.25	-.24	-		
	5. Rational style	-.07	.32*	-.21	.24	-	
	6. Experiential style	-.14	-.03	.17	-.11	-.14	-
Feature Space	1. Learning	-					
	2. User exp. (UEQ)	.16	-				
	3. Object I. style	-.39*	.17	-			
	4. Spatial I. style	.52***	.10	-.24	-		
	5. Rational style	.27	.11	-.21	.24	-	
	6. Experiential style	-.21	-.04	.17	-.11	.24	-

*$p < .05$, **$p < .01$, *** $p < .001$

The above correlation matrix (Table 5) shows significant correlation between the rational style and UEQ scores, $r(41) = .32$, $p < .05$, within the Objective Space condition. On the other hand, there were significant correlations between objective imagery style and learning ($r(33) = -.39$, $p < .05$), and spatial imagery style and learning ($r(33) = .52$, $p < .001$). This provided rough overview of the potential relationships to be examined.

Results from comparisons of DDSS usage outcomes between field knowledge groups are reported in Table 6. When comparing DDSS learning outcomes between high field knowledge (STEM) and low field knowledge (non-STEM) students, overall high field knowledge students performed better on the learning test than low field knowledge students. However, this relationship is only significant for scores regarding the Feature Space ($t(12) = 2.57$, $p = .02$). In regards to user experience, analysis showed a main effect of having high field knowledge on rating on the UEQ questionnaire such that high field knowledge students gave higher ratings of user experience for both the Objective Space (*t*(23) = 4.25, *p* < .001) and Feature Space conditions (*t*(33) = 3.33, *p* = .002). This mostly confirms H1a an H1b where prior field knowledge predicts DDSS learning and user experience. However, only learning outcomes were moderated by interface design, thus only H1c was only partially supported.

Table 6. Comparisons of DDSS usage outcomes by field knowledge groups

Outcome	Field knowledge (*n*)	Design decision support system (DDSS)		t-test
		Objective Space (Literal)	Feature Space (Abstract)	
Learning M(SD)	High: STEM (10)	18.79 (2.64)	19.67 (2.12)	*t*(28)=1.39, *p*=.17
	Low: NonSTEM (24)	17.20 (2.97)	16.80 (3.22)	*t*(20)=-.21, *p*=.83
	t-test	*t*(17)=1.46, *p*=.16	*t*(12)=2.57*, *p*=.02	
User experience M(SD)	High: STEM (31)	4.81 (.85)	4.50 (.06)	*t*(57)=-1.29, *p*=.20
	Low: NonSTEM (12)	3.69 (.75)	3.65 (1.02)	*t*(21)=-.14, *p*=.89
	t-test	t(23)=4.25***, p=.0003	t(33)=3.33**, p=0.002	

p* < .05, ** *p* <.01, * *p* < .001, **** *p* < .0001
H1a: Field Knowledge → Learning
H1b: Field Knowledge → User Exp
H1c: Field Knowledge → Learning & User exp | DDSS

Looking at cognitive style by field knowledge groups (Table 7), the analysis showed significant differences in object-spatial cognitive style between high field knowledge (STEM) and low field knowledge (non-STEM) students, which aligned with findings from previous findings (Chabris et al., 2006). On average, high field knowledge students have significantly higher scores on the spatial imagery scale ($t(30) = 2.41$, $p = .022$) and lower scores on the object imagery scale ($t(31) = -4.31$, $p < .001$), and the opposite relationships were observed for low field knowledge students. We also looked at cognitive style dominance, meaning if an individual scored higher on one dimension than another or if the individual scored equally on both dimensions. Analysis showed that high field knowledge students tend to be more Spatial dominant whereas low field knowledge students tend to be more object dominant. No significant differences in rational-experiential cognitive styles were observed.

Table 7. Comparisons of cognitive styles by field knowledge groups

		Field knowledge		
		High (STEM) n=32	Low (nonSTEM) n=13	t-test
Cognitive Styles M(SD)	Object Imagery	3.03 (.57)	3.67 (.40)	$t(31)=-4.31$***, $p=.0001$
	Spatial Imagery	3.71 (.56)	3.34 (.42)	t(30)=2.41*, p=.022
	Δ Obj.-Spat.	-.68 (.84)	.33 (.59)	t(32)=-4.60****, p<.0001
	Rational	3.86 (.489)	3.56 (.53)	$t(21)=1.75$, $p=.095$
	Intuitive	3.07 (.57)	3.64 (.57)	$t(20)=-.91$, $p=.37$
	Δ Ratio.-Intu.	.78 (.78)	.29 (.91)	$t(20)=1.71$, $p=.10$

*$p < .05$, ** $p < .01$, *** $p < .001$, **** $p < .0001$

Furthermore, 4 mixed model analyses (Model 1-4) with each containing one of the 4 cognitive style dimensions, field knowledge, and DDSS interface design were conducted to assess the effects of cognitive styles and field knowledge on learning (Table 8) and 4 additional mixed model analyses (Model 5-8) were conducted to assess their effects on user experience (Table 9). Analysis showed partial support for H1a, H3a, and H3c. Within Model 1, there was a main effect of object visualization style on overall learning *F*(60) = -2.20, *p* = .02, such that object visualizers tend to have lower learning outcomes (support for H3a). There also seemed to be an object visualization x field knowledge interaction effect such that lower object scores among high field knowledge (STEM) students are associated with higher learning outcomes, *F*(60) = -2.41, *p* = .01, whereas lower object scores among low field knowledge (non-STEM) students did not have a significant effect on learning outcomes (partial support for H3c). Looking at Model 2, two main effects were found to be significant. There was a main effect of spatial visualization (*F*(60) = 1.75, *p* = .02) and field knowledge (*F*(60) = -.68, *p* = .08) on general learning with no interaction effects were found in this model (support for H1a and H3a). Regarding Model 3, only field knowledge was found to have a main effect on learning, *F*(60) = -1.24, *p* = .002. Similarly, in Model 4, only field knowledge's main effect on learning was found, *F*(60)= -1.09, *p* = .003 (Support for H1a). Within Model 5, two significant main effects were found for object imagery (*F*(39) = 2.19, *p* = .03) and field knowledge (*F*(39) = .60, *p* = .0001) on user experience which provided partial support for H1b and H3b. In model 6, 7 and 8, only field knowledge show significant main effect on user experience (*F*(39) = -.42, *p* = .006, *F*(39) = -4.7, *p* = .001, *F*(39) = -.52, *p* = .0002, respectively) further partially supporting H1b.

Table 8. Effects of cognitive styles and field knowledge on learning: mixed model results

Mixed Model 1: Object, STEM, DDSS					Mixed Model 2: Spatial, STEM, DDSS				
Fixed Effects	B	SE	*F*	*p*	Fixed Effects	B	SE	*F*	*p*
[Object]	-2.20	.94	5.49	.02*	[Spatial]	1.75	.72	5.89	.02*
[STEM]	.05	.57	.01	.93	[STEM]	-.68	.38	3.13	.08
[DDSS]	-.29	.93	.26	.62	[DDSS]	-.08	.38	.05	.83
[Object×STEM]	-2.41	.94	6.58	.01*	[Spatial×STEM]	1.17	.72	2.66	.11
[Object×DDSS]	.55	.94	.34	.56	[Spatial×DDSS]	-.69	.72	.92	.34

[STEM×DDSS]	.08	.57	.02	.88	[STEM×DDSS]	.22	.38	.33	.57
[Object×STEM×DDSS]	.24	.94	.06	.80	[Spatial×STEM×DDSS]	.46	.72	.41	.53
Mixed Model 3: Rational, STEM, DDSS					Mixed Model 4: Experiential (Exp), STEM, DDSS				
Fixed Effects	B	SE	*F*	*p*	Fixed Effects	B	SE	*F*	*p*
[Rational]	-.34	.67	.26	.61	[Experiential]	-.48	.64	.57	.45
[STEM]	-1.24	.38	10.59	.002**	[STEM]	-1.09	.36	9.29	.003**
[DDSS]	-.00	.38	.00	.99	[DDSS]	-.16	.36	.21	.65
[Rational×STEM]	-.68	.67	1.03	.31	[Exp.×STEM]	.67	.64	1.11	.30
[Rational×DDSS]	-.67	.67	1.02	.32	[Exp.×DDSS]	.10	.64	.03	.87
[STEM×DDSS]	.25	.38	.43	.52	[STEM×DDSS]	.29	.36	.66	.42
[Rational×STEM×DDSS]	.83	.67	1.55	.22	[Exp.×STEM×DDSS]	.42	.64	.43	.51

*$p < .05$, ** $p < .01$, *** $p < .001$, **** $p < .0001$, DV: Learning (test score), random effect: participants' individual effects

Table 9. Effects of cognitive styles and field knowledge on user experience: mixed model results

Mixed Model 5: Object Imagery, STEM, DDSS					Mixed Model 6: Spatial Imagery, STEM, DDSS				
Fixed Effects	B	SE	*F*	*p*	Fixed Effects	B	SE	*F*	*p*
[Object]	2.19	.95	5.11	.03*	[Spatial]	.27	.28	.92	.34
[STEM]	.60	.27	18.17	.0001***	[STEM]	-.42	.14	8.48	.006**
[DDSS]	.06	.12	.29	.59	[DDSS]	.10	.10	1.07	.31
[Object×STEM]	-.07	.27	.07	.79	[Spatial×STEM]	.32	.28	1.30	.26
[Object×DDSS]	-.06	.20	.08	.77	[Spatial×DDSS]	.12	.19	.37	.55
[STEM×DDSS]	-.06	.12	.24	.63	[STEM×DDSS]	-.04	.10	.19	.67
[Object×STEM×DDSS]	.09	.20	.20	.66	[Spatial×STEM×DDSS]	.03	.19	.02	.89
Mixed Model 7: Rational, STEM, DDSS					Mixed Model 8: Experiential (Exp), STEM, DDSS				
Fixed Effects	B	SE	*F*	*p*	Fixed Effects	B	SE	*F*	*p*
[Rational]	.17	.24	.49	.49	[Experiential]	.14	.20	.50	.50
[STEM]	-.47	.13	12.15	.001**	[STEM]	-.52	.12	17.32	.0002***
[DDSS]	.07	.09	.59	.45	[DDSS]	.08	.09	.84	.36
[Rational×STEM]	.03	.24	.02	.90	[Exp.×STEM]	.32	.20	2.52	.12

[Rational×DDSS]	.13	.16	.68	.42	[Exp.×DDSS]	.03	.13	.16	.69
[STEM×DDSS]	-.06	.09	.42	.52	[STEM×DDSS]	-.07	.09	.72	.40
[Rational×STEM×DDSS]	-.17	.16	1.15	.29	[Exp.×STEM×DDSS]	.08	.14	.29	.59

p* < .05, ** *p* <.01, * *p* < .001, **** *p* < .0001, DV: User Experience, random effect: participants' individual effects

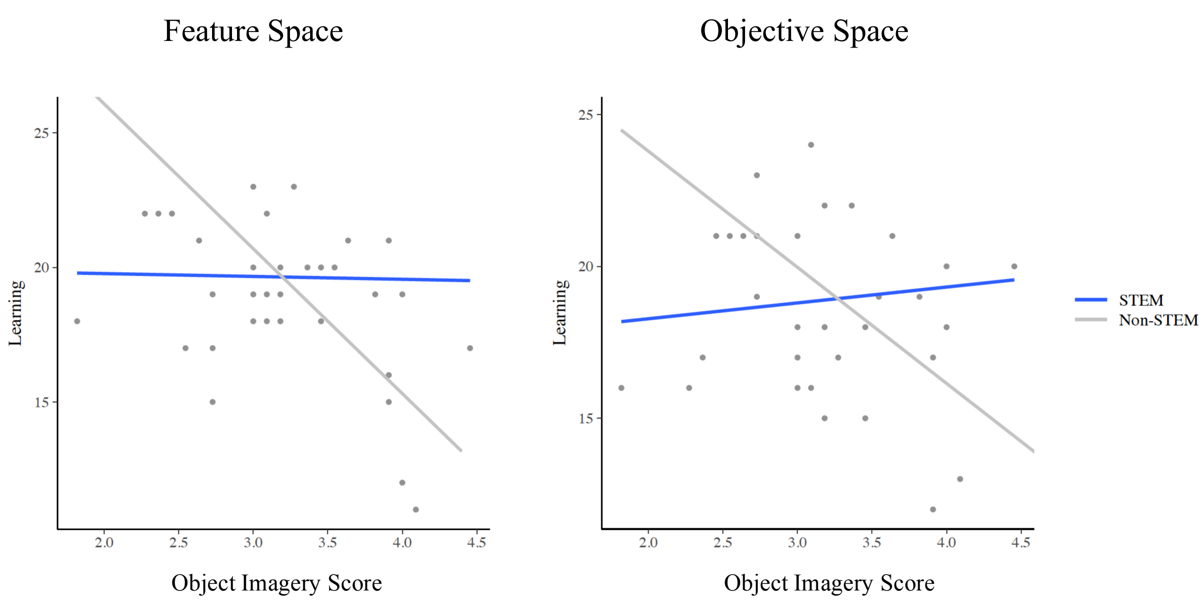

Figure 4. Regression plots of object imagery scores and learning outcomes for Feature (left) and Objective Space (right)

Regression analyses were conducted to assess the effects of cognitive style on learning and user experience between the two DDSS interfaces. Results show partial support for H3d such that only the effects of object-spatial cognitive style on learning within the feature space showed any significance and no support for H2 as no significant findings were found for rational-experiential cognitive styles. The regression plots in Figure 4 show interaction effects between object imagery scores and field knowledge on learning outcomes. In both plots, higher object scores predict lower learning outcomes among low field knowledge (non-STEM) students; however, this relationship is only significant within the Feature Space (p = 0.0044). However, among high field learning (STEM) student, higher object scores show better learning outcomes within the Objective Space, which suggest partial support for H3e. In this case, object imagery was a significant predictor of learning outcomes within the Feature Space, $b = -1.82$, $t(32) = -2.39$, $p = .023$; spatial imagery was a stronger predictor with $b = 2.54$, $t(32) = .52$, $p = .0015$; lastly, when considering imagery dominance, the difference in object and spatial imagery scores also significantly predicted learning within the Feature Space, $b = -1.72$, $t(32) = -.57$, $p < .001$.

Table 10. Significant effects of cognitive styles on learning in Feature Space: regression analysis results

IV: Cognitive Style	DV: Learning with Feature DDSS			
	b	β	t	p
Object imagery	-1.82	-.39	-2.39	**.023***
Spatial Imagery	2.54	.52	3.46	**.0015****
Δ Obj.-Spat. Imagery	-1.72	-.57	-3.94	**.0004*****

*p < .05, ** p <.01, *** p < .001, **** p < .0001

3.7. Summary of Findings

Table 5. Study 1 hypotheses summary

Hypothesis			Support
	H1a	Field Knowledge → Learning	Partial
H1	H1b	Field Knowledge → User Exp	Partial
	H1c	Field Knowledge → Learning & User exp | DDSS	No
	H2a	Rat. Exp. → Learning	No
	H2b	Rat. Exp. → User Exp	No
H2	H2c	Rat. Exp. → Learning & User Exp | Field Knowledge	No
	H2d	Rat. Exp. → Learning & User Exp | DDSS	No
	H2e	Rat. Exp. → Learning & User Exp | Field Knowledge, DDSS	No
	H3a	Obj. Spa. → Learning	Partial
	H3b	Obj. Spa. → User Exp	Partial
H3	H3c	Obj. Spa. → Learning & User Exp | Field Knowledge	Partial
	H3d	Obj. Spa. → Learning & User Exp | DDSS	No
	H3e	Obj. Spa. → Learning & User Exp | Field Knowledge, DDSS	Partial

The main findings of the first study show a significant effect of field knowledge on complex DDSS learning and user experience, which also aligned with previous findings that were discussed in the literature review, which showed the main effect of field knowledge on learning and user experience outcomes (Chen, 2002; Florance & Marchionini, 1995; Ghinea & Chen, 2003; Patel et al., 1998) as well as the interaction effect of visualization style and information presentation on user learning outcomes (Thomas & Mckay, 2010). Higher field knowledge, which in this case was determined by STEM major fields, predicts higher learning outcomes and better user experience scores, which supports H1a and H1b. In terms of cognitive style, only the dimensions of object-spatial visualization styles were found to have significant effect whereas rational-experiential cognitive styles did not have any significant influence. Thus, H2 was not supported whereas H3a and H3b were partially supported. Object scores were found to have a main effect on learning and user experience; spatial scores were found to have a main effect on learning alone. Furthermore, there is an interaction effect of visualization style, field knowledge and DDSS interface design where higher object imagery scores can predict lower learning outcomes among non-STEM majors within the feature space condition. However, within the STEM majors, higher object imagery scores may predict better learning outcomes in the object space condition and thus suggest partial support for H3e.

4. Study 2 : Protocol Analysis

4.1. Protocol Analysis

For Study 2, a video-based protocol analysis was conducted to further explore the differences in design processes between different user groups. Protocol analysis is a research technique widely used to study design and human problem solving processes (Ericsson & Simon, 1993; Someren, Barnard, & Sandberg, 1994). Someren et al. (1994) has introduced a systematic approach to conducting protocol studies (Figure 5). In summary, the series of steps include (1) building a psychological model that predicts behavior outcomes, (2) designing and administering experiments to capture protocols, (3) transcribing protocols, (4) generating coding schemes, (5) encoding protocols, (6) then analyzing and reporting results. In this study, video protocols without audio were analyzed, thus only observable behaviors were coded in the coding scheme.

4.2. Data Collection

In Study 1, user interactions with the DDSS were recorded with a screen capture software. These videos documented the processes through which the users engaged with the DDSS interfaces and they were used in the protocol analysis to be coded and analyzed. Due to the time intensive coding process of video protocol analysis, only 20 videos were selected to be included in this study. The aim of the study was to examine the behavior differences between user groups. Since the results from the previous study have indicated that cognitive visualization style had a significant effect on user performance, the videos were chosen to include users at the two extreme ends in terms of both their learning scores and cognitive style scores. Thus, users were ranked based on their learning scores and their cognitive visualization scores and the final selection were made within the top and bottom 25% of rankings. The specific selection criteria were presented in Table 12**.** Then their corresponding screen captured videos were trimmed for analysis.

Table 12. Data collection levels

	High Learning	Low Learning
Objective Space (Literal) Condition	Within top 25% of learning scores and object visualization scores (N=5)	Within bottom 25% of learning scores and object visualization scores (N=5)
Feature Space (Abstract) Condition	Within top 25% of learning scores and spatial visualization scores (N=5)	Within bottom 25% of learning scores and spatial visualization scores (N=5)

4.3. Protocol Coding Scheme

A behavior coding scheme was developed for the protocol analysis. The items were developed from consulting the iFEED creators to learn what possible behaviors could take place and from examining the initial codings of a few sample protocols. Initially, the goal was to map the behaviors to an existing design process model such as the Function-Behavior-Structure model (Gero & Kannengiesser, 2006; Qian & Gero, 1996). However, the entire experiment was embedded in the structure component of the model and thus did not exactly fit the needs of the study; thus, only behaviors were included in the coding scheme.

The two different experimental conditions required slightly different coding schemes as different actions were possible within each condition. The coding scheme for the Objective Space (literal) condition included only 3 items: *Scan Design (SD), Inspect Design (ID), and Modify Design (MD)*. The coding scheme for the Feature Space (abstract) condition consisted of

10 items because more actions were possible: *Scan Design (SD), Inspect Design (ID), Modify Design (MD), Scan Feature (SF), Inspect Feature (IF), Modify Feature (MF), Increase Specificity (IS), Increase Coverage (IC), Objective Space (OS) and Feature Space (FS).*

Certain items were concurrent, meaning that they could occur simultaneously; for example, *Scan Design (SD)* and *Objective Space (OS)* were concurrent because while one was scanning designs he or she also had to be in the Objective Space. Other items were mutually exclusive, which meant that they could not occur at the same time; behaviors such as *Scan Design (SD)* and *Inspect Design (ID)* were mutually exclusive as one could only do one or the other at a time. Most behaviors in the coding schemes were duration-based behaviors that spanned a certain time frame. The frequency-based behaviors only coded the number of incidents a specific behavior occurred; the *Increase Specificity (IS)* behavior coded the number of incidents the user clicked on the "Increase Specificity" button. The detailed coding schemes are listed in the tables below:

Table 13. Objective Space condition coding scheme

Behavior	Code Type	Definition	
Scan Design (SD)	Duration	When the user hovers the cursor over designs for less than 5 seconds in the objective space	
Inspect Design (ID)	Duration	When the user pauses on a specific design for more than 5 seconds (including evaluating a modified design)	Mutually Exclusive
Modify Design (MD)	Duration	When the user adds, subtracts, or moves components of a design	

Table 14. Feature Space condition coding scheme

Behavior	Code Type	Definition	
Scan Design (SD)	Duration	When the user rapidly hovers the cursor over multiple designs in the objective space	Mutually Exclusive
Inspect Design (ID)	Duration	When the user pauses on a specific design for more than 5 seconds (including evaluating a modified design)	
Modify Design (MD)	Duration	When the user adds, subtracts, or moves components of a design	
Scan Feature (SF)	Duration	When the user rapidly hovers the cursor over multiple features in the feature space	
Inspect Feature (IF)	Duration	When the user pauses on a specific feature for more than 5 seconds (including pauses on features after modification)	
Modify Feature (MF)	Duration	When the user adds, subtracts, or moves components of a feature	
Increase Specificity (IS)	Frequency	When the user clicks the “increase specificity” button	Concurrent
Increase Coverage (IC)	Frequency	When the user clicks the “increase coverage” button	
Objective Space (OS)	Duration	When the user is in the objective space interface	Mutually Exclusive
Feature Space (FS)	Duration	When the user is in the feature space interface	

4.4. Procedure

The Observer XT by Noldus was used throughout the coding process. It is a research software that allows the researcher to easily encode different time segments of a video into different behaviors. Within the software, each behavior in the established coding scheme was bound to a quick-key on the keyboard specified by the researcher. As the video played, quick-keys were pressed at different times in the video to map that time segment to specific behaviors to count frequencies of actions. The 20 videos were coded by 2 research assistants: the author and an undergraduate student. A training session was held prior to the coding process to ensure coding consistency. During the training session, both coders coded the same video entry; the coding criteria for each behavior was discussed and agreed upon. A video from the Feature Space condition was chosen as it covered all possible behaviors including the ones for the Objective Space condition.

Then we each completed the coding for the 20 videos separately over the course of 2 months. The two sets of codes are compared in the Observer XT software. The initial inter-observer agreement calculated by the software ranged from 47.15% to 97.56% with an average of 87.60%. The low average was due to an outlier value as only 3 videos had inter-observer agreements below 80%. The agreements were calculate base on the number of segments a behavior has occurred and the total time. The Cohen's kappa values for inter-observer agreement also ranged from 0.06 to 0.96 with an average of 0.81. The videos with lower than 80% agreements were recoded after research assistants discussed the disputes. As for the videos with high agreements percentages, the set coded by the author was used as the final version.

4.5. Hypotheses

As mentioned in the literature review (Blajenkova, Kozhevnikov, & Motes, 2006; Kozhevnikov et al., 2005), object visualizers prefer to process information in terms of physical appearances and they like to encode information globally as a single perceptual unit; thus, the author hypothesized that they will spend more time looking at the individual satellite designs. On the other hand, spatial visualizers prefer to process information in terms of its relationships, transformations and in sequence of components; therefore, it is hypothesized that they will spend more time scanning satellite constellation designs to examine the relationships between satellite constellation designs, the transformations, and the effects of individual components. Specifically, the following hypotheses are made:

- H4: High performing designers who also have high object imagery scores in the Objective Space condition will exhibit more design inspecting behavior than their low performing counterparts. (High Performance → High ID | Objective Space)
- H5: High performing designers who also have high spatial imagery scores in the Feature Space condition will exhibit more feature scanning behavior than their low performing counterparts. (High Performance → High SF | Feature Space)
- H6: High performing designers in both conditions are associated with more modifying behavior than their low performing counterparts as it implies understanding and testing of knowledge, specifically high performing designers will show more design modifying behavior in the objective Space Condition and more feature modifying behavior in the Feature Space condition. (High Performance → High MD | Objective Space and High Performance → High MF | Feature Space)

4.6. Results

To assess these hypotheses, the Wilcoxon test and the Fisher's exact test were used to examine the significance of group differences. These tests were chosen to accommodate the small sample sizes (N=10 within each condition) and the author's inability to assume normality in the variable distributions and same variability between groups. For similar reasons, regressions were not modeled for analysis.

Table 15. Objective Space condition: correlation matrix

	Behavior Outcomes						Learning & Cognitive Scores		
	SD	ID	MD	SD/ID	MD/SD	MD/ID	Learning Score	Object I. Score	Spatial I. Score
SD	-								
ID	-0.79**	-							
MD	-0.73*	0.21	-						
SD/ID	0.97****	-0.86**	-0.60	-					
MD/SD	-0.73*	0.45	0.75*	-0.60	-				
MD/ID	-0.62	0.07	0.97****	-0.50	0.60	-			
Learning Score	-0.06	0.17	0.09	-0.07	0.39	0.05	-		
Object I. Score	0.01	0.22	-0.07	-0.09	0.17	-0.09	0.82**	-	
Spatial I. Score	-0.10	0.29	-0.38	-0.14	-0.06	-0.47	-0.46	-0.46	-

*$p < .05$, ** $p <.01$, *** $p < .001$, **** $p < .0001$

Regarding results from the Objective Space condition, a correlation matrix was plotted to investigate the relationships between learning scores, cognitive visualization scores and the behavior outcome values. There was significant correlation between *Scan Design (SD)* and the other two behaviors variables: $r(10) = -.79$, $p < .01$ for *Inspect Design (ID)* and $r(10) = -.73$, $p < .05$ for *Modify Design (MD)*. This was to be expected as the experiment had a fixed duration and these behaviors were mutually exclusive, thus more time spent on one behavior would imply less time spent on another. The significant correlations between the behavior outcome values and their ratios were also to be expected. Specifically, *Scan Design (SD)* was significantly correlated to the *SD/ID* ($r(10) = .97$, $p < .0001$) and *MD/SD* ($r(10) = -.73$, $p < .05$), *Inspect Design (ID)* was correlate with *SD/ID* ($r(10) = -.86$, $p < .01$), and *Modify Design (MD)* was correlate with both *MD/SD* ($r(10) = .75$, $p < .05$) and *MD/ID* ($r(10) = .97$, $p < .0001$). Furthermore, there was a significant correlation between learning scores and object imagery scores ($r(10) = .82$, $p < .01$)

which was in alignment with the findings from the previous study. No other significant correlations were found and this could be due to the extremely small sample size of the study.

Table 16. Objective Space condition: performance group differences

	High Performance	Low Performance	Significance Testing
Learning Score	*M*=19.00 *SD*=1.00	*M*=16.20 *SD*=0.45	*p*=0.0079**
Object I. Score	*M*=3.84 *SD*=0.49	*M*=2.53 *SD*=0.55	*p*=0.0079**
Spatial I. Score	*M*=3.49 *SD*=0.47	*M*=4.11 *SD*=0.22	*p*=0.0397*
Gender	Male:2 (40%) Female:3 (60%)	Male:4 (80%) Female:1 (20%)	*p*=0.5238
Scan Design	*M*=178.35 *SD*=94.64	*M*=205.09 *SD*=104.58	*p*=1.0000
Inspect Design	*M*=340.16 *SD*=58.22	*M*=322.15 *SD*=64.79	*p*=1.0000
Modify Design	*M*=69.84 *SD*=68.28	*M*=43.49 *SD*=47.76	*p*=0.6723
SD/ID	*M*=0.56 *SD*=0.34	*M*=0.71 *SD*=0.50	*p*=0.8345
MD/SD	*M*=1.11 *SD*=1.92	*M*=0.39 *SD*=0.59	*p*=0.8325
MD/ID	*M*=0.21 *SD*=0.21	*M*= 0.13 *SD*=0.13	*p*=0.6723

*$p < .05$, ** $p <.01$, *** $p < .001$, **** $p < .0001$

H4: High Performance → High ID | Objective Space

H6: High Performance → High MD | Objective Space

and High Performance → High MF | Feature Space

Table 16 examined group differences using the Wilcoxon test for continuous variables and the Fisher's exact test for categorical variables. The results allowed the author to reject the null hypothesis that the learning (*p*=.0079), object imagery (*p*=.0079), and spatial imagery scores (*p*=.0379) were the same between the two groups because of the nature of the group selection process. The rest of the comparisons did not yield statistically significant results and the Fisher's test failed to assume independence between learning and gender groups. However, looking at the raw group means, high performers (*M*=340.16 *SD*=58.22) seemed to have a tendency to spend more time on inspecting designs than low performers (*M*=322.15 *SD*=64.79), and the ratio of SD/ID was lower for high performers (*M*=0.56 *SD*=0.34) than low performers (*M*=0.71 *SD*=0.50). This observation suggested possible support for H4. The high performers (*M*=43.49 *SD*=47.76) also had a higher group mean on time spent modifying designs than the low performers (*M*=69.84 *SD*=68.28), which implied possible evidence for H6.

The videos were also segmented into quarters to further examine the trends of behaviors over time compared between the two performance groups. The following tables and figures show the trends and quarterly group means for each of the behavior outcomes measured in seconds.

Table 17. Quarterly scan design group comparison (Objective Space condition)

	High Performance	Low Performance	Significance Testing
1st Quarter	*M*=43.12 *SD*=36.80	*M*=65.48 *SD*=21.86	*p*=0.2963
2nd Quarter	*M*=50.83 *SD*=41.32	*M*=42.81 *SD*=40.91	*p*=0.6761
3rd Quarter	*M*=51.66 *SD*=0.268	*M*=36.60 *SD*=40.68	*p*=0.4020
4th Quarter	*M*=33.32 *SD*=27.42	*M*=60.21 *SD*=33.57	*p*= 0.2101

$*p < .05$, $** p <.01$, $*** p < .001$, $**** p < .0001$

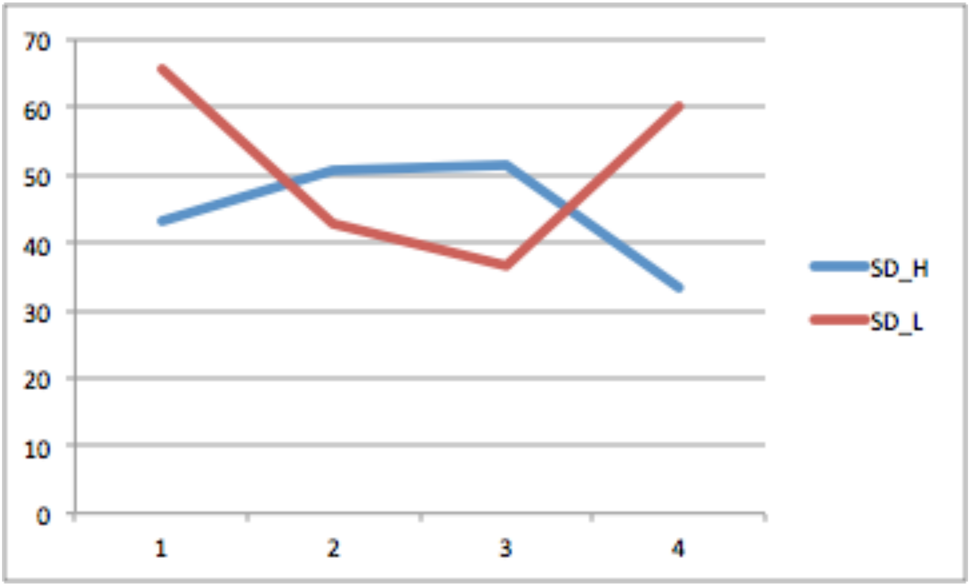

Figure 5. Quarterly scan design data (blue: high performing; red: low performing)

Looking at *Scan Design (SD)*, none of the quarterly group means between the high and low performing groups were significantly different from 0. However, looking at the line plot of the quarterly group means over time, there seemed to be opposite relationships between the two groups. Low performers seemed to do a lot of scanning at the beginning and the end with a decrease in the middle, whereas high performers seemed to do less scanning at the beginning and the end but with an increase in the middle.

Table 18. Quarterly inspect design data group comparison (Objective Space condition)

	High Performance	Low Performance	Significance Testing
1st Quarter	M=84.96 SD=30.18	M=67.20 SD=23.16	p=0.2963
2nd Quarter	M=72.71 SD=21.07	M=85.55 SD=29.17	p=0.5309
3rd Quarter	M=88.17 SD=39.87	M=100.47 SD=29.57	p=0.5309
4th Quarter	M=94.31 SD=16.93	M=68.92 SD=37.08	p= 0.2101

$^*p < .05$, $^{**} p < .01$, $^{***} p < .001$, $^{****} p < .0001$

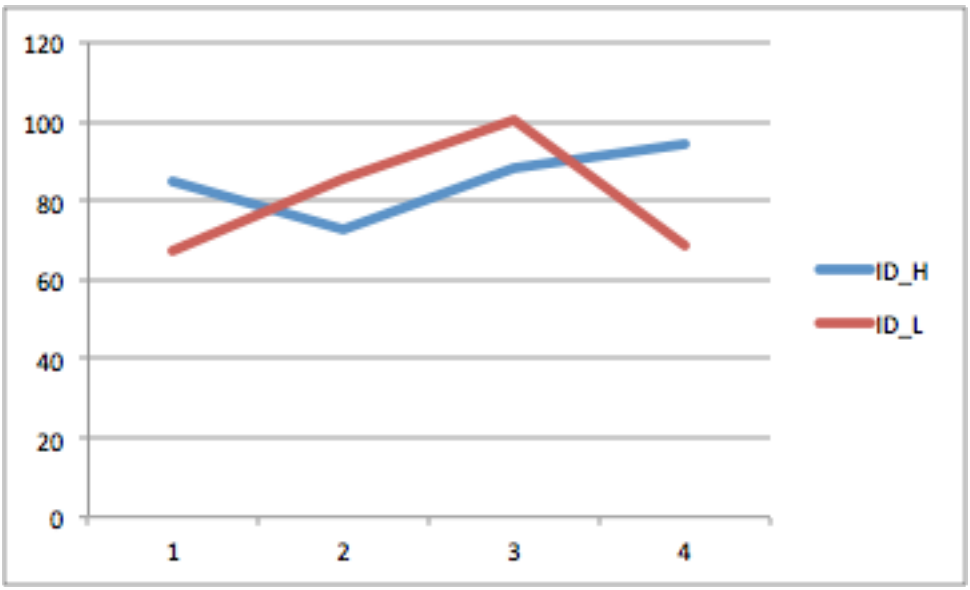

Figure 6. Quarterly inspect design data

On the other hand, *Inspect Design (ID)* shows the opposite trends than *Scan Design (SD)*. Though none of the group mean differences were statistically significant, it did imply that high performers tend to inspect more in the beginning and the end which contrasted with low performers' tendency to inspect more in the middle.

Table 19. Quarterly modify design data group comparison (Objective Space condition)

	High Performance	Low Performance	Significance Testing
1st Quarter	*M*=10.76 *SD*=13.45	*M*=2.30 *SD*=5.13	*p*=0.2393
2nd Quarter	*M*=18.18 *SD*=25.46	*M*=21.64 *SD*=22.78	*p*=0.5900
3rd Quarter	*M*=10.16 *SD*=12.45	*M*=12.93 *SD*=16.40	*p*=1.0000
4th Quarter	*M*=22.45 *SD*=30.80	*M*=6.63 *SD*=10.63	*p*= 0.7241

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$, $^{****}p < .0001$

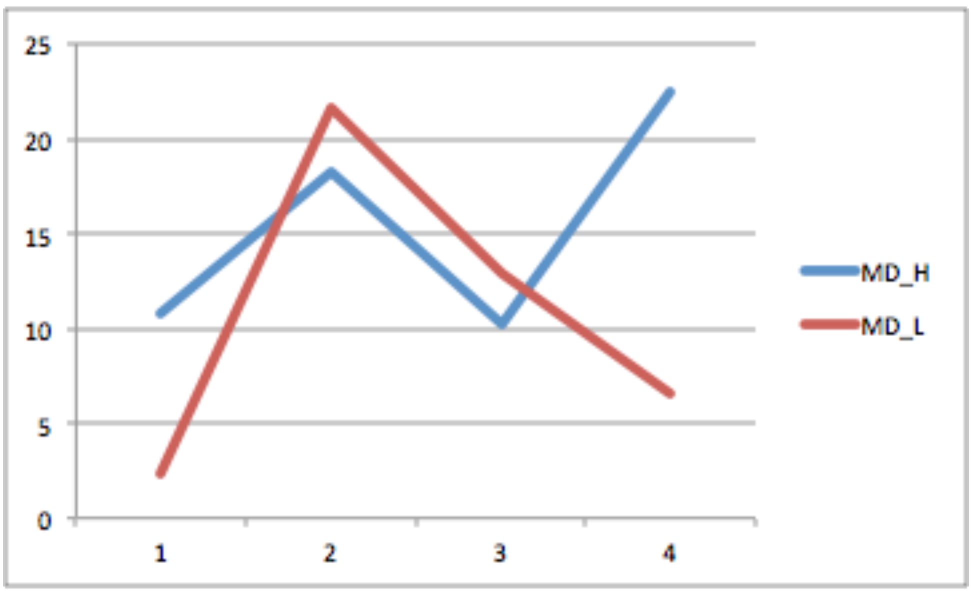

Figure 7. Quarterly modify design data

Lastly, no group mean differences were found to be statistically significant for *Modify Design (MD)*. The trend exhibited a dramatic divergence in the last quarter with high performers increasing time spent on modifying designs and low performers decreasing time spent on such behavior.

Table 20. Feature (abstract) space condition: correlation matrix

S	O	L	SD/ID	MF/IF	MF/SF	SF/IF	IC/IS	OS/FS	FS	OS	IS	IC	MF	IF	SF	ID	SD	
-0.1929	0.5395	-0.5156	0.94*	-0.29	-0.29	0.02	0.19	0.21	-0.45	0.48	-0.34	0.04	-0.33	-0.28	-0.11	0.20	-	SD
0.4554	0.0173	0.2310	-0.6426	0.16	0.16	-0.27	-0.02	0.99 ****	-0.96 ****	0.95 ****	-0.43	-0.45	-0.04	-0.50	-0.75 *	-		SD
-0.3693	-0.2228	-0.2579	0.7989	-0.2911	-0.2987	0.7933 **	-0.3896	-0.7103 *	0.7167 *	-0.7188	0.8269 **	0.2092	-0.1253	-0.0573	-			SD
-0.2801	0.1173	0.0472	0.1223	0.1409	0.1278	-0.5668	0.7334*	-0.5159	0.5096	-0.5257	-0.3955	0.5310	0.2803	-				IF
0.5156	-0.6142	0.5986	-0.5654	0.9578	0.9488 ****	-0.3337	-0.0674	-0.1440	0.1182	-0.1138	-0.1623	0.1051	-					MF
-0.3312	0.2889	0.0028	0.5052	0.0263	0.0089	-0.0508	0.5514	-0.4737	0.3859	-0.3754	-0.0861	-						IC
-0.1860	-0.3816	-0.1055	0.3087	-0.1999	-0.1889	0.8851 ***	-0.6964 *	-0.4121	0.4857	-0.4976	-							IS
0.3486	0.2125	0.0140	-0.4437	0.0846	0.0905	-0.2287	0.0501	0.9368 ****	-0.9904 ****	-								OS
-0.3902	-0.1710	-0.0744	0.5523	-0.0864	-0.0886	0.2415	-0.0614	-0.9387 ****	-									FS
0.3793	0.0613	0.1591	-0.5186	0.0341	0.0389	-0.2148	-0.0285	-										OS/FS
-0.2486	0.6048	-0.1946	0.3754	-0.0977	-0.1108	-0.5855	-											IC/IS
-0.2339	-0.1048	-0.3584	0.7850	-0.3657	-0.3573	-												SF/IF
0.5665	-0.5647	0.5907	-0.6712	0.9985 ****	-													MF/SF
0.5807	-0.5759	0.6149	-0.6819	-														MF/IF
-0.9793 **	0.844 *	-0.8007	-															SD/ID
0.6987	-0.6789	-																L
-0.3775	-																	O
-																		S

*$p < .05$, ** $p < .01$, *** $p < .001$, **** $p < .0001$

Regarding the Feature Space condition results, a correlation matrix was also created to examine the relationships between the variables. Majority of the significant correlations were due to either the presence of ratios or the nature of the variables; for example, *MF/SF* was significantly correlated with *Modify Feature (MF)* ($r(10) = .95$, $p < .0001$) as *MF/SF* is a ratio of *Modify Feature (MF),* and *Inspect Design (ID)* was significantly correlated with *Objective Space (OS)* ($r(10) = .95$, $p < .0001$) because inspecting design was a behavior that occurred in the objective space. Other significant correlations were between object imagery scores and *SD/ID* ($r(10) = .84$, $p < .05$), and between spatial imagery scores and *SD/ID* ($r(10) = -.98$, $p < .01$).

Table 21. Feature Space condition: performance group differences

	High Performance	Low Performance	Significance Testing
Learning Score	*M*=21.00 *SD*=1.00	*M*=14.20 *SD*=2.59	*p*= 0.0117*
Object Score	*M*=2.91 *SD*=0.45	*M*=3.46 *SD*=0.75	*p*= 0.2963
Spatial Score	*M*=4.40 *SD*= 0.13	*M*=3.02 *SD*= 0.45	*p*= 0.0119*
Gender	Male:5 (100%) Female:0 (0%)	Male:1 (20%) Female:4 (80%)	*p*= 0.0476*
Scan Design	*M*=33.17 *SD*=37.43	*M*=58.81 *SD*=59.48	*p*= 0.5258
Inspect Design	*M*=111.58 *SD*=170.84	*M*=15.949 *SD*=22.080	*p*= 0.2652
Scan Feature	*M*=115.36 *SD*=57.29	*M*=164.21 *SD*=58.55	*p*= 0.2101
Inspect Feature	*M*=196.75 *SD*=103.50	*M*=223.16 *SD*=134.87	*p*=1.0000
Modify Feature	*M*=53.45 *SD*=58.87	*M*=0.00 *SD*=0.00	*p*= 0.0254*
Objective Space	*M*=142.53 *SD*=192.93	*M*=70.73 *SD*=82.06	*p*=0.8340

Feature Space	*M*=453.32 *SD*=194.72	*M*=535.53 *SD*=67.69	*p*=1.0000
Increase Coverage	*M*=3.60 *SD*=1.82	*M*=4.00 *SD*=2.35	*p*=1.0000
Increase Specificity	*M*=8.20 *SD*=4.76	*M*=12.40 *SD*=10.57	*p*=0.6733
OS/FS	*M*=0.82 *SD*=1.55	*M*=0.15 *SD*=0.18	*p*=0.8340
IC/IS	*M*=0.51 *SD*=0.24	*M*=0.64 *SD*=0.56	*p*=1.0000
SF/IF	*M*=0.60 *SD*=0.22	*M*=1.11 *SD*=0.91	*p*=0.8345
MF/SF	*M*=0.48 *SD*=0.49	*M*=0.00 *SD*=0.00	*p*=0.0254*
MF/IF	*M*=0.23 *SD*=0.22	*M*=0.00 *SD*=0.00	*p*=0.0254*
SD/ID	*M*=0.64 *SD*=0.78	*M*=3.08 *SD*=1.00	*p*=0.1489

*$p < .05$, ** $p <.01$, *** $p < .001$, **** $p < .0001$

Looking at performance group differences, first, the performance outcomes and the spatial imagery scores were significantly different from 0 between the two groups by design. The Fisher's exact test on gender x performance group showed that the two variables were significantly independent of each other. In addition, there was a significant group difference between the high and low performers in terms of *Modify Feature (MF)*, *MF/SF*, and *MF/IF*, which supported H6. Looking at group differences in terms of scanning behavior, the high performers had less times on *Scan Feature (SF)* as well as *Scan Design (SD)* than low performers. This was the opposite than what H5 predicted.

The videos of the Feature Space conditions were also segmented into quarters for further analysis.

Table 22. Quarterly scan design data group comparison (Feature Space condition)

	High Performance	Low Performance	Significance Testing
1st Quarter	*M*=11.27 *SD*=16.12	*M*=29.90 *SD*=50.99	*p*=0.6558
2nd Quarter	*M*=0.47 *SD*=1.06	*M*=11.12 *SD*=17.88	*p*=0.4407
3rd Quarter	*M*=10.43 *SD*=9.98	*M*=8.94 *SD*=12.57	*p*=1.0000
4th Quarter	*M*=11.00 *SD*=15.33	*M*=8.86 *SD*=12.30	*p*= 0.9063

$^*p < .05$, $^{**}\ p <.01$, $^{***}\ p < .001$, $^{****}\ p < .0001$

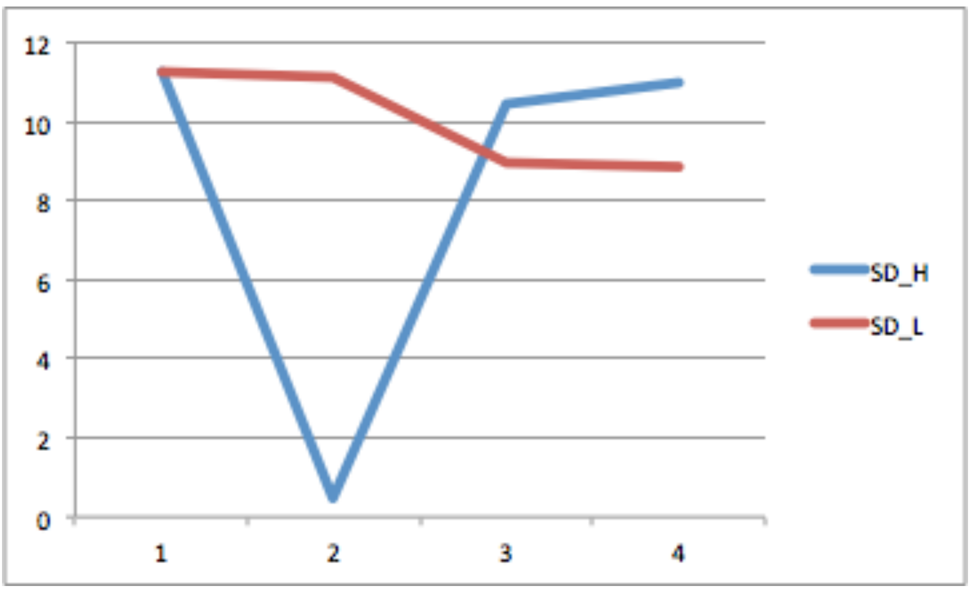

Figure 8. Quarterly scan design data (Feature Space condition)

Scan Design (SD) had a very distinct difference within the second quartile with the high performing group dropping down to almost 0. However, the null hypotheses that these quartile group differences were significantly different from 0 cannot be rejected.

Table 23. Quarterly inspect design data group comparison (Feature Space condition)

	High Performance	Low Performance	Significance Testing
1st Quarter	*M*=13.51 *SD*=30.21	*M*=6.43 *SD*=8.82	*p*=0.7972
2nd Quarter	*M*=28.72 *SD*=64.22	*M*=7.83 *SD*=12.11	*p*=0.7972
3rd Quarter	*M*=38.28 *SD*=56.11	*M*=1.39 *SD*=3.10	*p*=0.1579
4th Quarter	*M*=31.07 *SD*=31.67	*M*=0.30 *SD*=0.67	*p*= 0.1579

$^*p < .05$, $^{**}\ p < .01$, $^{***}\ p < .001$, $^{****}\ p < .0001$

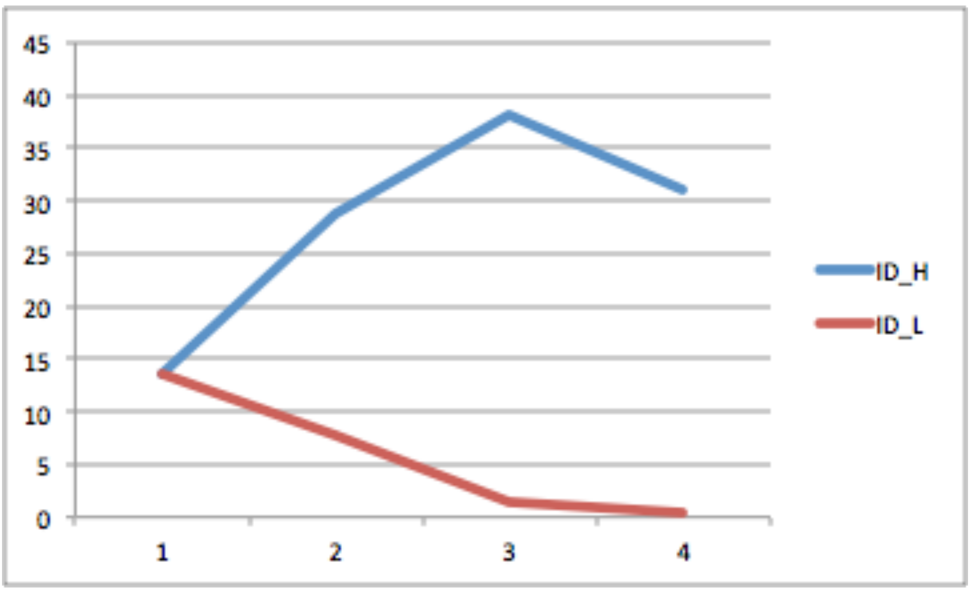

Figure 9. Quarterly inspect design data (Feature Space Condition)

The trends of *Inspect Design (ID)* showed an interesting divergence since the second quartile. Consistently, the high performers seemed to have spent more time on inspecting designs than the lower performers throughout the last three quarters of the study. However, no group differences were significantly different from 0 as well.

Table 24. Quarterly scan feature data group comparison

	High Performance	Low Performance	Significance Testing
1st Quarter	*M*=40.81 *SD*=24.27	*M*=29.22 *SD*=18.18	*p*=0.2492
2nd Quarter	*M*=24.84 *SD*=24.50	*M*=49.96 *SD*=36.71	*p*=0.4034
3rd Quarter	*M*=25.40 *SD*=26.71	*M*=44.47 *SD*=43.49	*p*=0.4633
4th Quarter	*M*=24.31 *SD*=23.91	*M*=40.56 *SD*=15.19	*p*= 0.1437

*$p < .05$, ** $p <.01$, *** $p < .001$, **** $p < .0001$

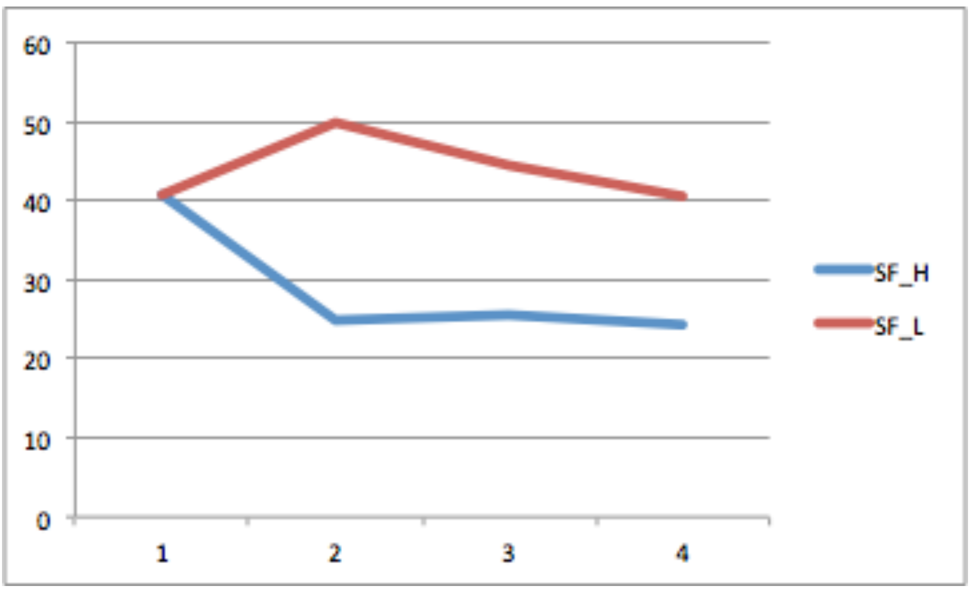

Figure 10. Quarterly scan feature data

The *Scan Feature (SF)* plot also diverged starting from the second quartile and stayed relatively consistent for the high performers and decreased slightly for the low performers. Low performers seemed to have consistently spent more time on scanning features starting from the second quartile. Again, no group differences are significantly different from 0.

Table 25. Quarterly inspect feature data group comparison

	High Performance	Low Performance	Significance Testing
1st Quarter	*M*=30.91 *SD*=20.73	*M*=55.05 *SD*=39.51	*p*=0.3457
2nd Quarter	*M*=24.84 *SD*=24.50	*M*=49.96 *SD*=36.71	*p*=0.5485
3rd Quarter	*M*=55.70 *SD*=42.48	*M*=49.62 *SD*=51.30	*p*=1.0000
4th Quarter	*M*=56.58 *SD*=35.30	*M*=53.46 *SD*=32.70	*p*=1.0000

$*p < .05$, $** p < .01$, $*** p < .001$, $**** p < .0001$

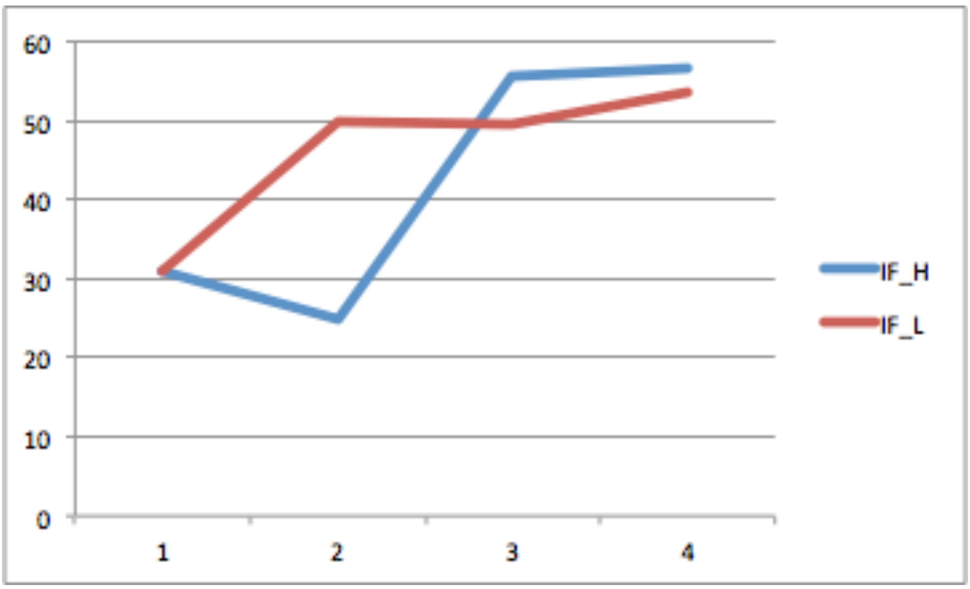

Figure 11. Quarterly inspect feature data

Looking at *Inspect Feature (IF)*, both groups started relatively low and spent more time on inspecting features at the end. For high performers, the time spent on inspecting features decreased a little then increased in the end; whereas for low performers, the increase was relatively consistent. No p-values for any of the group mean differences reached significant levels.

Table 26. Quarterly modify feature data group comparison

	High Performance	Low Performance	Significance Testing
1st Quarter	*M*=7.56 *SD*=13.91	*M*=0.00 *SD*=0.00	*p*=0.1797
2nd Quarter	*M*=15.63 *SD*=29.42	*M*=0.00 *SD*=0.00	*p*=0.1797
3rd Quarter	*M*=16.57 *SD*=24.06	*M*=0.00 *SD*=0.00	*p*=0.0720
4th Quarter	*M*=14.19 *SD*=20.22	*M*=0.00 *SD*=0.00	*p*=0.1797

$^*p < .05$, $^{**} p < .01$, $^{***} p < .001$, $^{****} p < .0001$

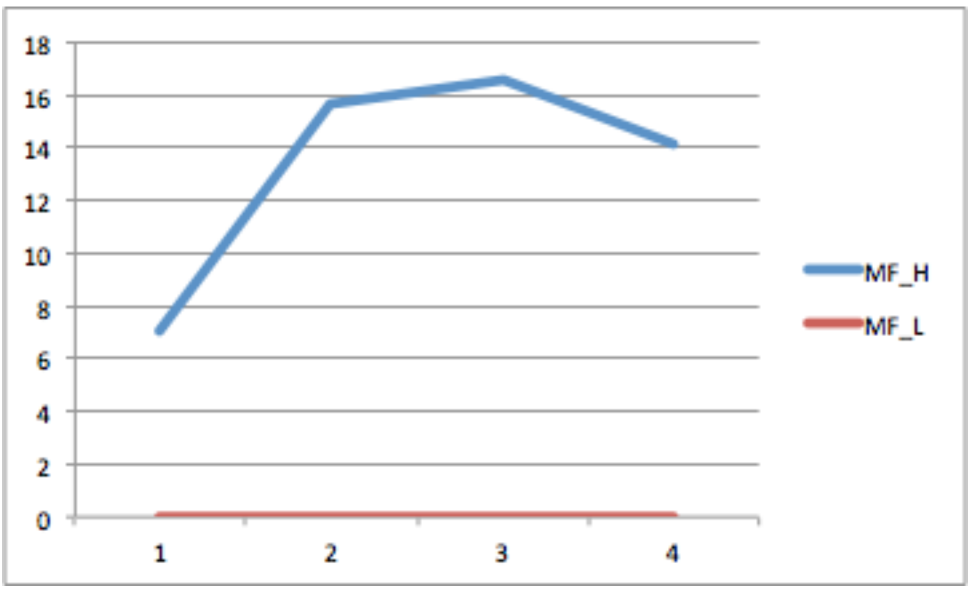

Figure 12. Quarterly modify feature data

For *Modify Feature (MF)*, the low learners consistently did not modify any features throughout the experiment, whereas the high performers spent a lot of time modifying features during the middle of the study. However, the Wilcoxon test did not yield any significant results.

Table 27. Quarterly Feature Space data group comparison

	High Performance	Low Performance	Significance Testing
1st Quarter	*M*=118.28 *SD*=43.00	*M*=106.16 *SD*=53.86	*p*=0.5309
2nd Quarter	*M*=120.00 *SD*=67.08	*M*=131.05 *SD*=29.97	*p*=0.7972
3rd Quarter	*M*=99.14 *SD*=62.80	*M*=144.80 *SD*=8.32	*p*=0.2652
4th Quarter	*M*=115.92 *SD*=41.04	*M*=153.52 *SD*=26.64	*p*= 0.2101

$*p < .05$, $** p <.01$, $*** p < .001$, $**** p < .0001$

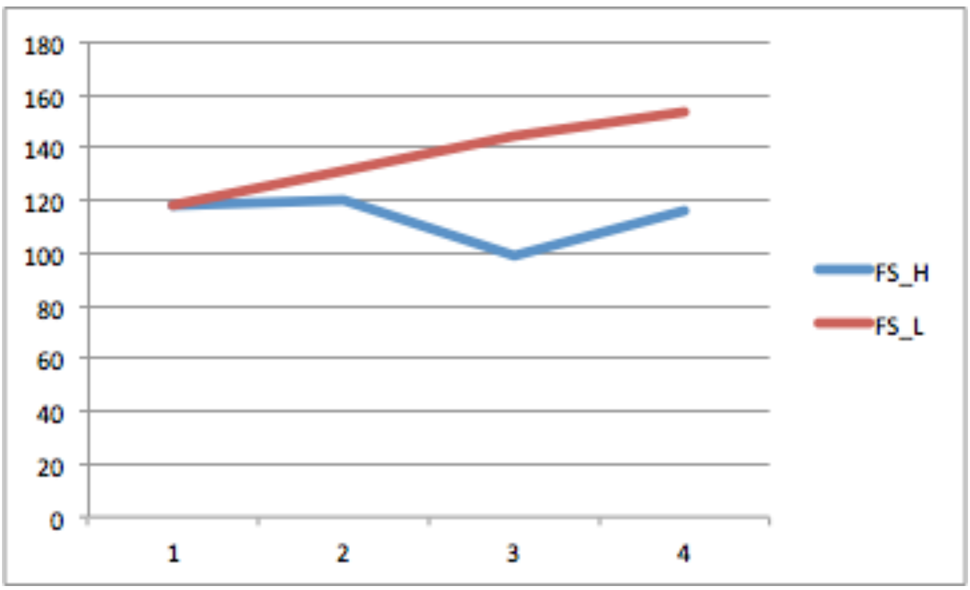

Figure 13. Quarterly Feature Space data

In the *Feature Space (FS)* plot, the high performers experienced a decrease in time spent within the Feature Space during the third quartile, and the low performers consistently increased time spent in the Feature Space throughout the study. The two groups were not found to be significantly different from each other.

Table 28. Quarterly Objective Space data group comparison

	High Performance	Low Performance	Significance Testing
1st Quarter	*M*=24.31 *SD*=38.88	*M*=37.54 *SD*=56.45	*p*=0.4506
2nd Quarter	*M*=30.00 *SD*=67.08	*M*=18.95 *SD*=29.97	*p*=0.7972
3rd Quarter	*M*=50.89 *SD*=62.80	*M*=5.21 *SD*=8.32	*p*=0.2652
4th Quarter	*M*=37.33 *SD*=36.77	*M*=10.07 *SD*=13.12	*p*= 0.3871

$^*p < .05$, $^{**}\ p <.01$, $^{***}\ p < .001$, $^{****}\ p < .0001$

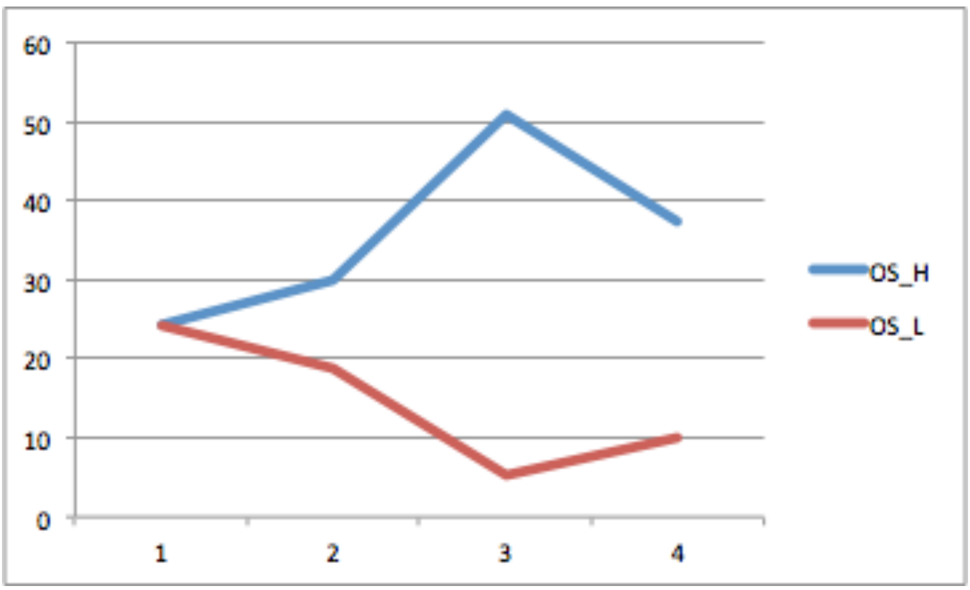

Figure 14. Quarterly Objective Space data

Lastly, the *Objective Space (OS)* trends also showed an interesting divergence starting at the second quartile and a small convergence in the fourth quartile. High performers spent more time in the objective space near the end than low performers, though these differences were not statistically significant.

4.7. Summary of Findings

Table 29. Study 2 hypotheses summary

Hypotheses		Support
H4	High Performance → High ID | Objective Space	No
H5	High Performance → High SF | Feature Space	No
H6	High Performance → High MD | Objective Space and High Performance → High MF | Feature Space	Partial

Few statistically significant results were observed from study 2, and it was to be expected due to the small sample size and the many limitations on data collection. In the Feature Space condition, the differences between the high and low learning groups on modifying behaviors were significantly different from 0, which provides support for H6. None of the other group differences were tested to be significant, thus no conclusive results could be drawn for the other hypotheses. However, many relationships were approaching significant levels and could provide potential insights into the relationships being examined. Looking at raw group means, there were potential crossover effects. For example, scanning behavior in the Objective space condition seemed to potentially support H4, where high performing designers exhibited more inspecting behavior, but in the Feature space condition the group means showed the opposite relationship. Similar conditional differences were found when testing for H5 as well where the scanning behavior between high performing and low performing designers differed based on condition. This could potentially imply a moderating effect by the DSS interface design, which should be investigated in future studies.

4.8. Additional Observation

In addition to the results reported above, there were other qualitative trends observed in the video protocols. A notable one being differences in *Increase Specificity (IS)* and *Increase Coverage (IC)* behaviors. In the Feature Space, users were able to click on buttons to increase specificity or coverage to generate new data points on the scatter plot. These new additions would represent new features shared between the selected group of satellite constellation designs that would either be shared by more satellite constellations within the selected group (coverage) or be more exclusive to the selected group (specificity). When engaging with the Feature Space, the order of which these two buttons were clicked differed between some of the high performers and low performers. In the case of many high performers, there was an alternation between increasing specificity and coverage where the two were balanced. However, many low performers often increased one aspect multiple times before switching to the other. This was an interesting observation as it potentially shows better prioritization among the high performers, as they are able to balance the desires characteristics of the outcomes.

5. Conclusion & Discussion

5.1. Conclusion

As discussed in the summery of findings, study 1 has confirmed the main effects of field knowledge on DDSS usage where higher field knowledge was associated with better learning and user experience outcomes. The objective-spatial visualization scores also had a significant influence on these outcomes such that individuals with high object imagery scores tend to have lower learning and user experience outcomes, where individuals with high spatial imagery scores were found to have better learning outcomes. There was also evidence for the three-way interaction effect between visualization style, field knowledge, and DDSS interface design.

In study 2, there were significant differences in modifying behavior between the high and low performing groups in the Feature Space condition such that high performers exhibited more modifying behavior. Though no other statistically significant relationships were observed, many trends shown in the results could provide possible insights into the relationships examined. The quarterly trends show potential differences in behaviors over time and many of the group mean differences imply possible influences of DDSS interface design on the relationship between performance and behavior.

5.2. Theoretical and Practical Implications

These preliminary findings confirmed findings from many previous studies while revealing new questions and insights. They also present exciting opportunities for potential applications in the field of DSS interface design to support complex design problem solving. The interaction effect between cognitive style, field knowledge and DDSS interface on learning and user experience suggests that information on these user characteristics can inform designers to optimize learning and user experience. Zooming in on the design processes of the user also gave us insights into what behaviors the systems should encourage to further support the different users. Ultimately, we aim to contribute to the effort of closing the gaps between different under-represented groups in engineering and design through researching how systems can be better designed to accommodate different cognitive styles, skill sets, and experiences. This would also better support collaboration across more diverse groups of engineers and designers, as diverse teams often are more successful at tackling complex issues.

5.3. Limitations and Future Directions

Given the available resources, there were many limitations to the study such as the small sample sizes and the lack of audio in the video samples. The audio files would provide insights into the motivations and rationales behind the users' actions. Therefore, in future studies, it would also be beneficial to add think aloud protocols to supplement the video protocols. This was something this study could not achieve due to limitations in terms of time and resources. Furthermore, the studies used a design problem in the context of satellite system design using iFEED with the participants being all university students. This greatly decreased the external validity of the findings. Moreover, this paper was unable to delve into the details of how individuals interacted with the interface and thus only general relationships were observed and no mechanisms could be concluded. However, the findings paved ways for future studies to further examine the underlying mechanisms as well as to explore the effects of different cognitive style dimensions, DSS interface designs, and design problem contexts.

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7. Appendix A: Pre-Experiment Survey

iFEED Individual Differences

Start of Block: Default Question Block

Please enter your name

____

Please select your gender

○ Male (1)

○ Female (2)

Please enter your major

____

Please select your year

○ freshman (1)

○ sophomore (2)

○ junior (3)

○ senior (4)

○ graduate (5)

Please enter your ethnicity

____

End of Block: Default Question Block

Start of Block: OSIQ

When entering a familiar store to get a specific item, I can easily picture the exact location of the target item, the shelf it stands on, how it is arranged and the surrounding articles.

- Definitely true (1)
- Probably true (2)
- Neither true nor false (3)
- Probably false (4)
- Definitely false (5)

My images are very colorful and bright.

- Definitely true (1)
- Probably true (2)
- Neither true nor false (3)
- Probably false (4)
- Definitely false (5)

I have photographic memory.

- Definitely true (1)
- Probably true (2)
- Neither true nor false (3)
- Probably false (4)
- Definitely false (5)

My graphic abilities would make a career in architecture relatively easy for me.

- Definitely true (1)
- Probably true (2)
- Neither true nor false (3)
- Probably false (4)
- Definitely false (5)

I prefer schematic diagrams and sketches when reading a textbook instead of colorful and pictorial illustrations.

- Definitely true (1)
- Probably true (2)
- Neither true nor false (3)
- Probably false (4)
- Definitely false (5)

I was very good in 3-D geometry as a student.

- Definitely true (1)
- Probably true (2)
- Neither true nor false (3)
- Probably false (4)
- Definitely false (5)

I normally do not experience many spontaneous vivid images; I use my mental imagery mostly when attempting to solve some problems like the ones in mathematics.

- Definitely true (1)
- Probably true (2)
- Neither true nor false (3)
- Probably false (4)
- Definitely false (5)

I have excellent abilities in technical graphics.

- Definitely true (1)
- Probably true (2)
- Neither true nor false (3)
- Probably false (4)
- Definitely false (5)

Architecture interests me more than painting.

- Definitely true (1)
- Probably true (2)
- Neither true nor false (3)
- Probably false (4)
- Definitely false (5)

I can close my eyes and easily picture a scene that I have experienced.

- Definitely true (1)
- Probably true (2)
- Neither true nor false (3)
- Probably false (4)
- Definitely false (5)

If I were asked to choose between engineering professions and visual arts, I would prefer engineering.

- Definitely true (1)
- Probably true (2)
- Neither true nor false (3)
- Probably false (4)
- Definitely false (5)

When thinking about an abstract concept (e.g., 'a building') I imagine an abstract schematic building in my mind or its blueprint rather than a specific concrete building.

- Definitely true (1)
- Probably true (2)
- Neither true nor false (3)
- Probably false (4)
- Definitely false (5)

My images are more like schematic representations for things events rather than like detailed pictures.

- Definitely true (1)
- Probably true (2)
- Neither true nor false (3)
- Probably false (4)
- Definitely false (5)

My mental images of different objects very much resemble the size, shape, and color of actual objects that I have seen.

- Definitely true (1)
- Probably true (2)
- Neither true nor false (3)
- Probably false (4)
- Definitely false (5)

I can easily sketch a blueprint for a building that I am familiar with.

- Definitely true (1)
- Probably true (2)
- Neither true nor false (3)
- Probably false (4)
- Definitely false (5)

In school, I had no problems with geometry.

- Definitely true (1)
- Probably true (2)
- Neither true nor false (3)
- Probably false (4)
- Definitely false (5)

My visual images are in my head all the time. They are just right there.

- Definitely true (1)
- Probably true (2)
- Neither true nor false (3)
- Probably false (4)
- Definitely false (5)

Sometimes my images are so vivid and persistent that it is difficult to ignore them.

- ◯ Definitely true (1)
- ◯ Probably true (2)
- ◯ Neither true nor false (3)
- ◯ Probably false (4)
- ◯ Definitely false (5)

When reading fiction, I usually form a clear and detailed mental picture of a scene or room that has been described.

- ◯ Definitely true (1)
- ◯ Probably true (2)
- ◯ Neither true nor false (3)
- ◯ Probably false (4)
- ◯ Definitely false (5)

When I imagine the face of a friend, I have a perfectly clear and bright image.

- ◯ Definitely true (1)
- ◯ Probably true (2)
- ◯ Neither true nor false (3)
- ◯ Probably false (4)
- ◯ Definitely false (5)

I can easily remember a great deal of visual details that someone else might never notice. For example, I would just automatically take some things in, like what color is a shirt someone wears or what color is a shirt someone wears or what color are his/her shoes.

- ○ Definitely true (1)
- ○ Probably true (2)
- ○ Neither true nor false (3)
- ○ Probably false (4)
- ○ Definitely false (5)

I find it difficult to imagine how a three-dimensional geometric figure would exactly look like when rotated.

- ○ Definitely true (1)
- ○ Probably true (2)
- ○ Neither true nor false (3)
- ○ Probably false (4)
- ○ Definitely false (5)

I am good in playing spatial games involving constructing from blocks and paper (e.g., Lego, Tetris, and Origami).

- Definitely true (1)
- Probably true (2)
- Neither true nor false (3)
- Probably false (4)
- Definitely false (5)

I enjoy picture with bright colors and unusual shapes like the ones in modern art.

- Definitely true (1)
- Probably true (2)
- Neither true nor false (3)
- Probably false (4)
- Definitely false (5)

When I hear a radio announcer or a DJ I’ve never actually seen, I usually find myself picturing what he or she might look like.

- Definitely true (1)
- Probably true (2)
- Neither true nor false (3)
- Probably false (4)
- Definitely false (5)

I can easily imagine and mentally rotate three-dimensional geometric figures.

- Definitely true (1)
- Probably true (2)
- Neither true nor false (3)
- Probably false (4)
- Definitely false (5)

My images are very vivid and photographic.

- Definitely true (1)
- Probably true (2)
- Neither true nor false (3)
- Probably false (4)
- Definitely false (5)

My images are more schematic than colorful and pictorial.

- Definitely true (1)
- Probably true (2)
- Neither true nor false (3)
- Probably false (4)
- Definitely false (5)

If I were asked to choose between studying architecture or visual arts I would choose visual arts.

- Definitely true (1)
- Probably true (2)
- Neither true nor false (3)
- Probably false (4)
- Definitely false (5)

I remember everything visually. I can recount what people wore to a dinner and I can talk about the way they sat and the way they looked probably in more detail than I would discuss what they said.

- Definitely true (1)
- Probably true (2)
- Neither true nor false (3)
- Probably false (4)
- Definitely false (5)

I have difficulty expressing myself in writing.

- Definitely true (1)
- Probably true (2)
- Neither true nor false (3)
- Probably false (4)
- Definitely false (5)

I tell jokes and stories better than most people.

- Definitely true (1)
- Probably true (2)
- Neither true nor false (3)
- Probably false (4)
- Definitely false (5)

Essay writing is difficult for me and I do not enjoy doing it at all.

- Definitely true (1)
- Probably true (2)
- Neither true nor false (3)
- Probably false (4)
- Definitely false (5)

My verbal skills are excellent.

- Definitely true (1)
- Probably true (2)
- Neither true nor false (3)
- Probably false (4)
- Definitely false (5)

When explaining something, I would rather give verbal explanations than make drawings or sketches (even when I have a pen and paper next to me).

- ◯ Definitely true (1)
- ◯ Probably true (2)
- ◯ Neither true nor false (3)
- ◯ Probably false (4)
- ◯ Definitely false (5)

When remembering a scene, I use verbal descriptions rather than mental pictures.

- ◯ Definitely true (1)
- ◯ Probably true (2)
- ◯ Neither true nor false (3)
- ◯ Probably false (4)
- ◯ Definitely false (5)

I have better than average fluency in using words.

- ◯ Definitely true (1)
- ◯ Probably true (2)
- ◯ Neither true nor false (3)
- ◯ Probably false (4)
- ◯ Definitely false (5)

I am always aware of sentence structure.

- Definitely true (1)
- Probably true (2)
- Neither true nor false (3)
- Probably false (4)
- Definitely false (5)

I enjoy being able to rephrase my thoughts in many ways for variety's sake in both writing and speaking.

- Definitely true (1)
- Probably true (2)
- Neither true nor false (3)
- Probably false (4)
- Definitely false (5)

When reading fiction, I usually form a clear and detailed mental picture of a scene or room that has been described.

- Definitely true (1)
- Probably true (2)
- Neither true nor false (3)
- Probably false (4)
- Definitely false (5)

End of Block: OSIQ

Start of Block: REI

I have a logical mind.

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

I prefer complex problems to simple problems.

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

I believe in trusting my hunches.

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

I am not a very analytical thinker.

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

I trust my initial feelings about people.

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

I try to avoid situations that require thinking in depth about something.

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

I like to rely on my intuitive impressions.

- ○ Completely False (21)
- ○ (22)
- ○ (23)
- ○ (24)
- ○ Completely True (25)

I don't reason well under pressure.

- ○ Completely False (21)
- ○ (22)
- ○ (23)
- ○ (24)
- ○ Completely True (25)

I don't like situations in which I have to rely on intuition.

- ○ Completely False (21)
- ○ (22)
- ○ (23)
- ○ (24)
- ○ Completely True (25)

Thinking hard and for a long time about something gives me little satisfaction.

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

Intuition can be a very useful way to solve problems.

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

I would not want to depend on anyone who described himself or herself as intuitive.

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

I am much better at figuring things out logically than most people.

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

I usually have clear, explainable reasons for my decisions.

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

I don't think it is a good idea to rely on one's intuition for important decisions.

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

Thinking is not my idea of an enjoyable activity.

- ○ Completely False (21)
- ○ (22)
- ○ (23)
- ○ (24)
- ○ Completely True (25)

I have no problem thinking things through carefully.

- ○ Completely False (21)
- ○ (22)
- ○ (23)
- ○ (24)
- ○ Completely True (25)

When it comes to trusting people, I can usually rely on my gut feelings.

- ○ Completely False (21)
- ○ (22)
- ○ (23)
- ○ (24)
- ○ Completely True (25)

I can usually feel when a person is right or wrong, even if I can't explain how I know.

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

Learning new ways to think would be very appealing to me.

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

I hardly ever go wrong when I listen to my deepest gut feelings to find an answer.

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

I think it is foolish to make important decisions based on feelings.

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

I tend to use my heart as a guide for my actions.

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

I often go by my instincts when deciding on a course of action.

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

I'm not that good at figuring out complicated problems.

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

I enjoy intellectual challenges.

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

Reasoning things out carefully is not one of my strong points.

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

I enjoy thinking in abstract terms.

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

I generally don't depend on my feelings to help me make decisions.

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

Using logic usually works well for me in figuring out problems in my life.

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

I think there are times when one should rely on one's intuition.

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

I don't like to have to do a lot of thinking.

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

Knowing the answer without having to understand the reasoning behind it is good enough for me.

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

Using my gut feeling usually works well for me in figuring out problems in my life.

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

I don't have a very good sense of intuition

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

If I were to rely on my gut feelings, I would often make mistakes.

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

I suspect my hunches are inaccurate as often as they are accurate.

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

My snap judgments are probably not as food as most people's.

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

I am not very good at solving problems that require careful logical analysis.

- Completely False (21)
- (22)
- (23)
- (24)
- Completely True (25)

I enjoy solving problems that require hard thinking.

- ○ Completely False (21)
- ○ (22)
- ○ (23)
- ○ (24)
- ○ Completely True (25)

End of Block: REI

Start of Block: VVIQ

For each item on this questionnaire, try to form a visual image, and consider your experience carefully. For any image that you do experience, rate how vivid it is using the five-point scale described below. If you do not have a visual image, rate vividness as '1'. Only use '5' for images that are truly as lively and vivid as real seeing. Please note that there are no right or wrong answers to the questions, and that it is not necessarily desirable to experience imagery or, if you do, to have more vivid imagery.

Think of some relative or friend whom you frequently see (but who is not with you at present) and consider carefully the picture that comes before your mind's eye. Then rate how vivid is the image for each of the items below.

The exact contour of face, head, shoulders and body

- ○ No image at all, you only "know" that you are thinking of the object (2)
- ○ Vague and dim (3)
- ○ Moderately clear and lively (4)
- ○ Clear and reaonably vivid (5)
- ○ Perfectly clear and vivid as real seeing (6)

Characteristic poses of head, attitudes of body etc.

- No image at all, you only "know" that you are thinking of the object (2)
- Vague and dim (3)
- Moderately clear and lively (4)
- Clear and reaonably vivid (5)
- Perfectly clear and vivid as real seeing (6)

The precise carriage, length of step etc., in walking

- No image at all, you only "know" that you are thinking of the object (2)
- Vague and dim (3)
- Moderately clear and lively (4)
- Clear and reaonably vivid (5)
- Perfectly clear and vivid as real seeing (6)

The different colours worn in some familiar clothes

- No image at all, you only "know" that you are thinking of the object (2)
- Vague and dim (3)
- Moderately clear and lively (4)
- Clear and reaonably vivid (5)
- Perfectly clear and vivid as real seeing (6)

Visualise a rising sun. Consider carefully the picture that comes before your mind's eye. Then rate how vivid is the image for each of the items below.

The sun rising above the horizon into a hazy sky

- ◯ No image at all, you only "know" that you are thinking of the object (2)
- ◯ Vague and dim (3)
- ◯ Moderately clear and lively (4)
- ◯ Clear and reaonably vivid (5)
- ◯ Perfectly clear and vivid as real seeing (6)

The sky clears and surrounds the sun with blueness

- ◯ No image at all, you only "know" that you are thinking of the object (2)
- ◯ Vague and dim (3)
- ◯ Moderately clear and lively (4)
- ◯ Clear and reaonably vivid (5)
- ◯ Perfectly clear and vivid as real seeing (6)

Clouds. A storm blows up with flashes of lightning

- No image at all, you only "know" that you are thinking of the object (2)
- Vague and dim (3)
- Moderately clear and lively (4)
- Clear and reaonably vivid (5)
- Perfectly clear and vivid as real seeing (6)

A rainbow appears

- No image at all, you only "know" that you are thinking of the object (2)
- Vague and dim (3)
- Moderately clear and lively (4)
- Clear and reaonably vivid (5)
- Perfectly clear and vivid as real seeing (6)

Think of the front of a shop which you often go to. Consider the picture that comes before your mind's eye. Then rate how vivid is the image for each of the items below.

The overall appearance of the shop from the opposite side of the road

- No image at all, you only "know" that you are thinking of the object (2)
- Vague and dim (3)
- Moderately clear and lively (4)
- Clear and reaonably vivid (5)
- Perfectly clear and vivid as real seeing (6)

A window display including colours, shapes and details of individual items for sale

- No image at all, you only "know" that you are thinking of the object (2)
- Vague and dim (3)
- Moderately clear and lively (4)
- Clear and reaonably vivid (5)
- Perfectly clear and vivid as real seeing (6)

You are near the entrance. The colour, shape and details of the door.

- No image at all, you only "know" that you are thinking of the object (2)
- Vague and dim (3)
- Moderately clear and lively (4)
- Clear and reaonably vivid (5)
- Perfectly clear and vivid as real seeing (6)

You enter the shop and go to the counter. The counter assistant serves you. Money changes hands

- No image at all, you only "know" that you are thinking of the object (2)
- Vague and dim (3)
- Moderately clear and lively (4)
- Clear and reaonably vivid (5)
- Perfectly clear and vivid as real seeing (6)

Finally think of a country scene which involves trees, mountains and a lake. Consider the picture that comes before your mind's eye. Then rate how vivid is the image for each of the items below.

The contours of the landscape

- No image at all, you only "know" that you are thinking of the object (2)
- Vague and dim (3)
- Moderately clear and lively (4)
- Clear and reaonably vivid (5)
- Perfectly clear and vivid as real seeing (6)

The colour and shape of the trees

- ○ No image at all, you only "know" that you are thinking of the object (2)
- ○ Vague and dim (3)
- ○ Moderately clear and lively (4)
- ○ Clear and reaonably vivid (5)
- ○ Perfectly clear and vivid as real seeing (6)

The colour and shape of the lake

- ○ No image at all, you only "know" that you are thinking of the object (2)
- ○ Vague and dim (3)
- ○ Moderately clear and lively (4)
- ○ Clear and reaonably vivid (5)
- ○ Perfectly clear and vivid as real seeing (6)

A strong wind blows on the trees and on the lake causing waves in the water

- ○ No image at all, you only "know" that you are thinking of the object (2)
- ○ Vague and dim (3)
- ○ Moderately clear and lively (4)
- ○ Clear and reaonably vivid (5)
- ○ Perfectly clear and vivid as real seeing (6)

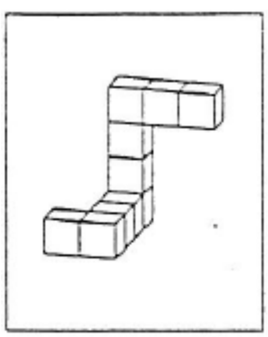
End of Block: VVIQ

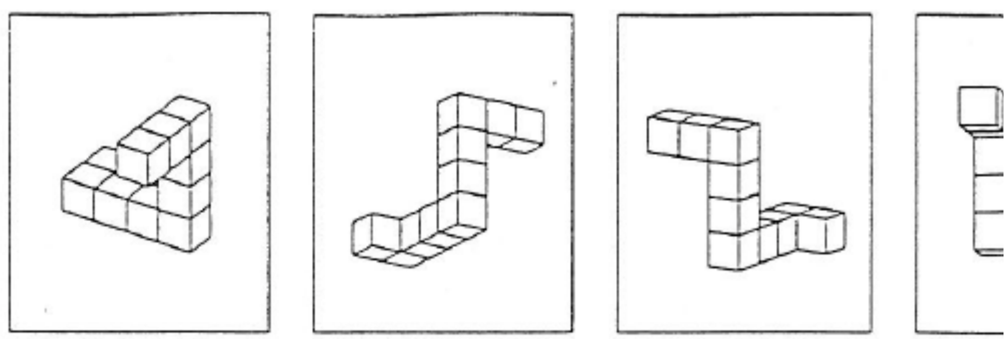
Start of Block: MRT

Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Each question below shows an image of a block object on the left. Within the group of 4 images on the right, there are two images that reflect a rotated version of the object on the left. From the leftmost image in the group, the images are numbered 1, 2, 3, and 4. Please indicate which 2 images are the rotated versions.

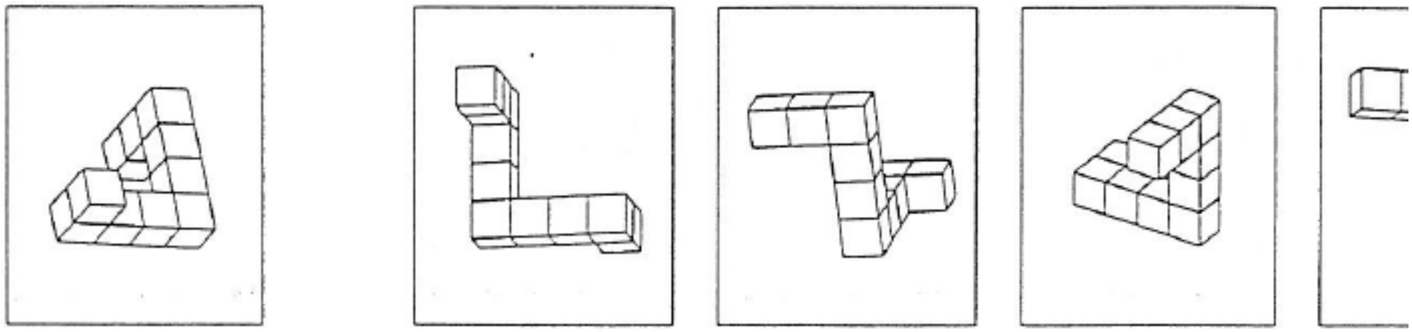
Please do not pause during this portion of the experiment.





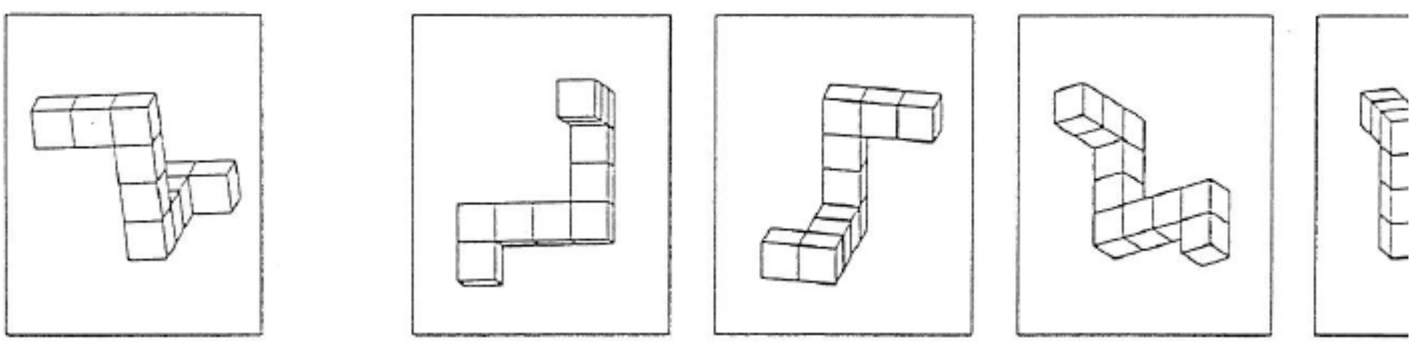
which two images are the rotated versions of the object on the left?

- [ ] 1 (1)
- [ ] 2 (2)
- [ ] 3 (3)
- [ ] 4 (4)



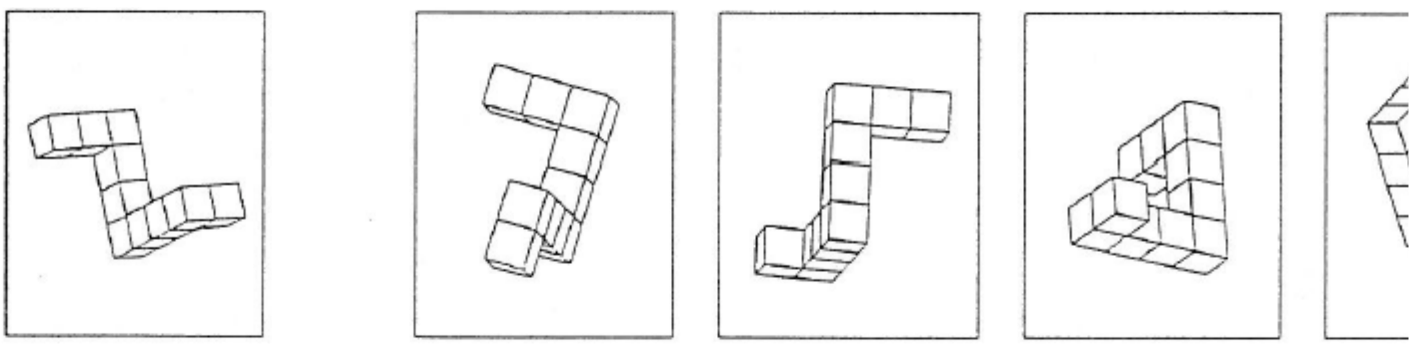
which two images are the rotated versions of the object on the left?

- [ ] 1 (1)
- [ ] 2 (2)
- [ ] 3 (3)
- [ ] 4 (4)



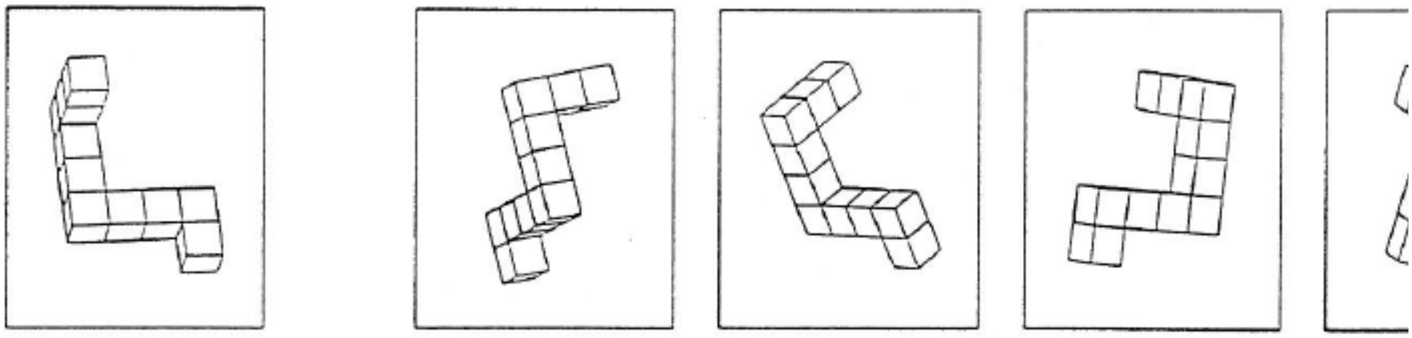
which two images are the rotated versions of the object on the left?

- 1 (1)
- 2 (2)
- 3 (3)
- 4 (4)



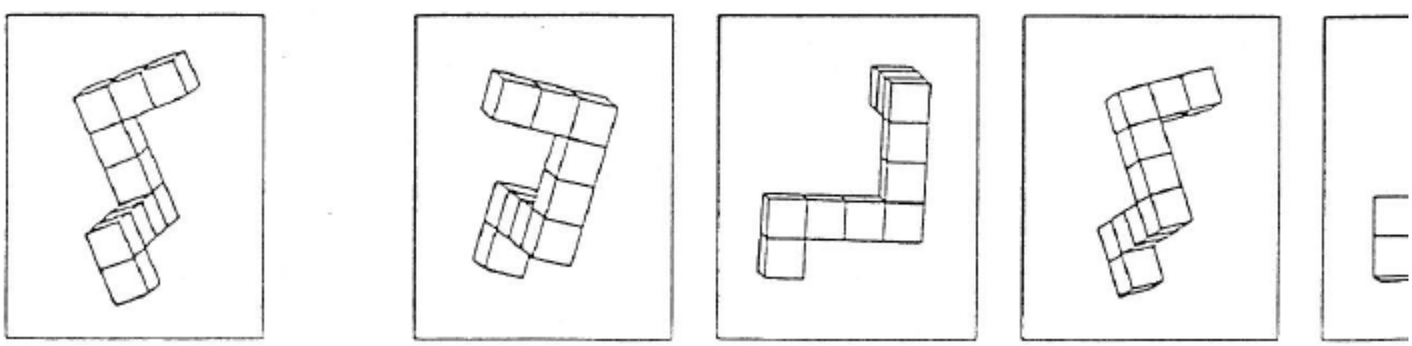
which two images are the rotated versions of the object on the left?

- 1 (1)
- 2 (2)
- 3 (3)
- 4 (4)



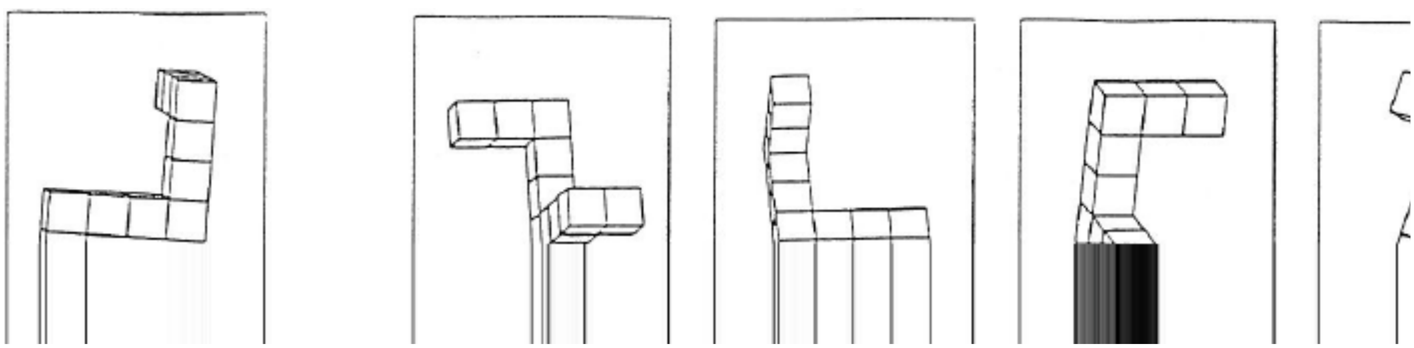
which two images are the rotated versions of the object on the left?

- [ ] 1 (1)
- [ ] 2 (2)
- [ ] 3 (3)
- [ ] 4 (4)



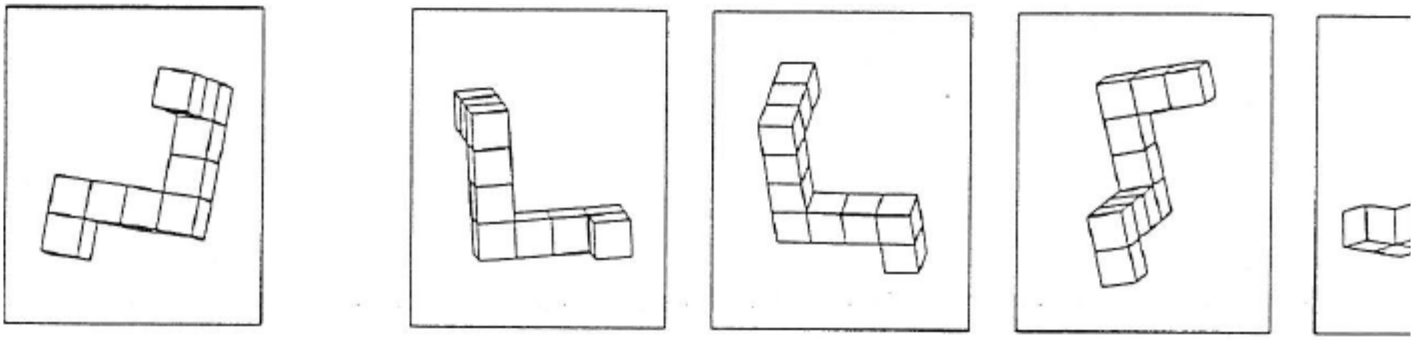
which two images are the rotated versions of the object on the left?

- 1 (1)
- 2 (2)
- 3 (3)
- 4 (4)



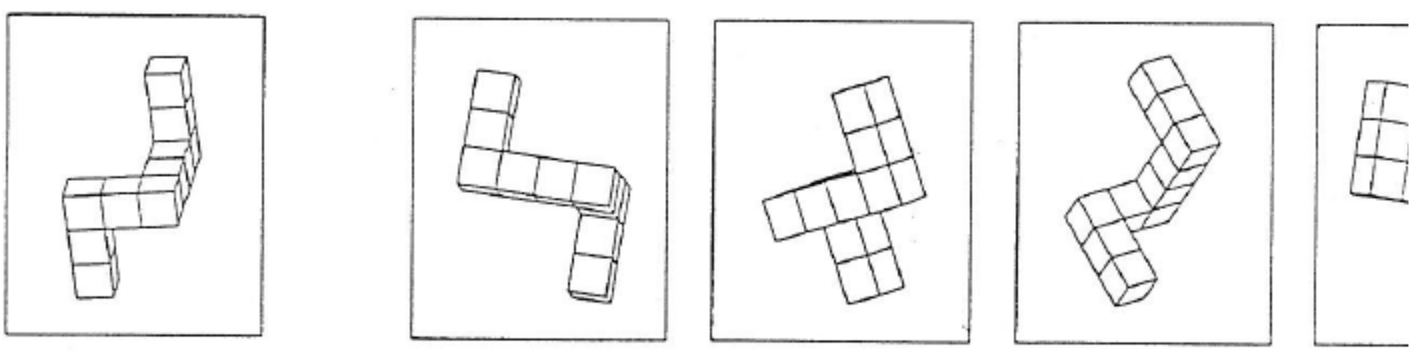
which two images are the rotated versions of the object on the left?

- 1 (1)
- 2 (2)
- 3 (3)
- 4 (4)



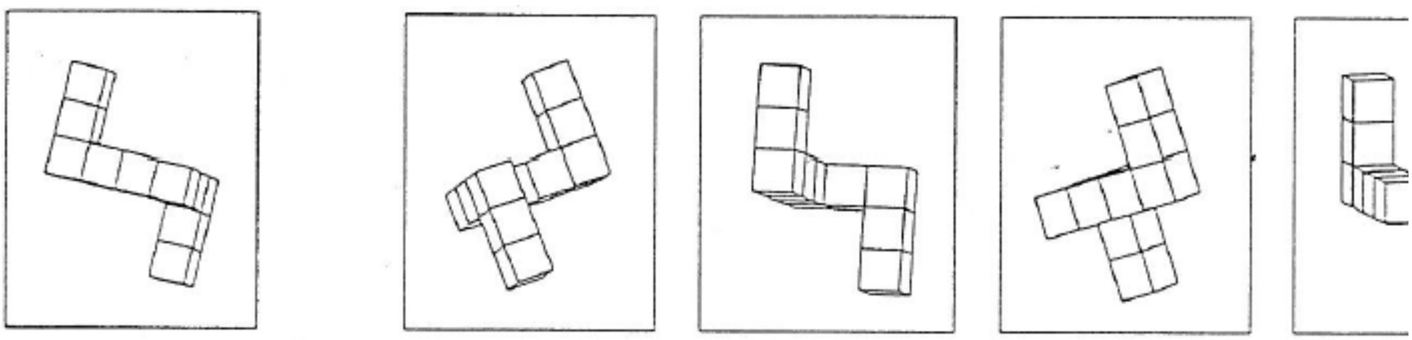
which two images are the rotated versions of the object on the left?

- 1 (1)
- 2 (2)
- 3 (3)
- 4 (4)



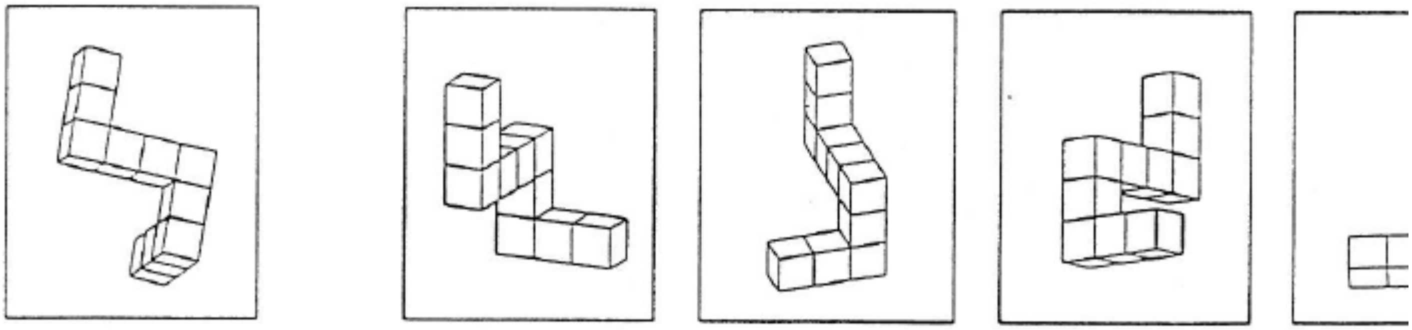
which two images are the rotated versions of the object on the left?

- [ ] 1 (1)
- [ ] 2 (2)
- [ ] 3 (3)
- [ ] 4 (4)



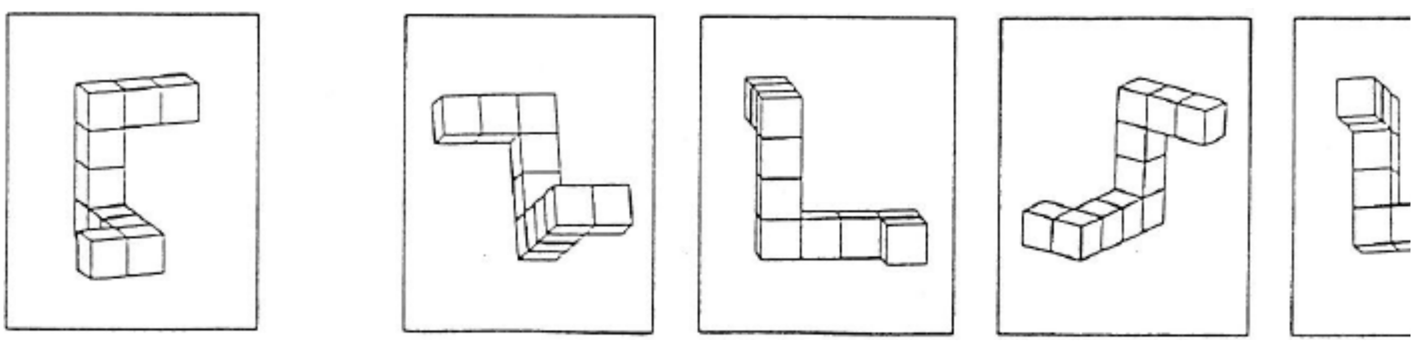
which two images are the rotated versions of the object on the left?

- [ ] 1 (1)
- [ ] 2 (2)
- [ ] 3 (3)
- [ ] 4 (4)



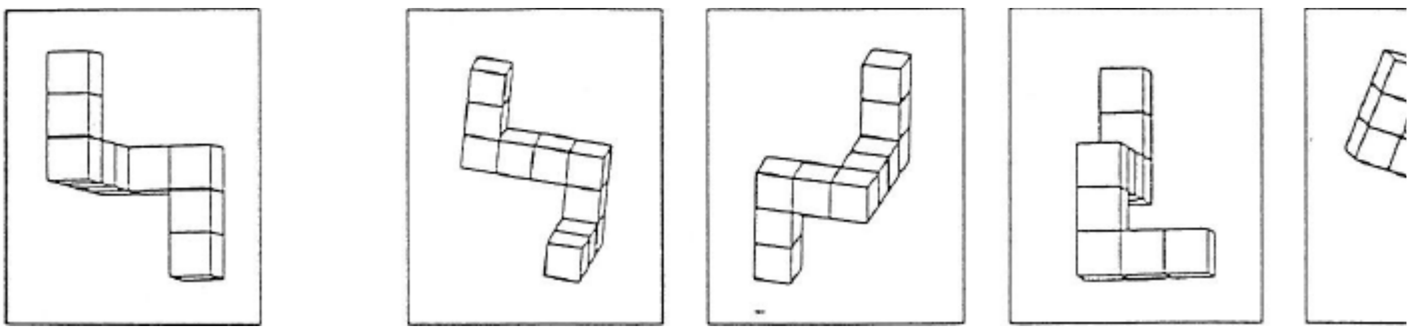
which two images are the rotated versions of the object on the left?

- 1 (1)
- 2 (2)
- 3 (3)
- 4 (4)



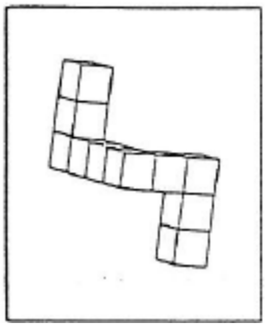
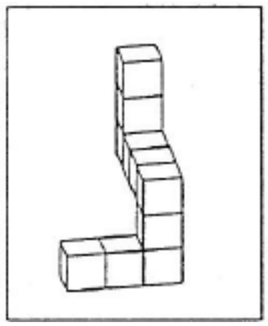
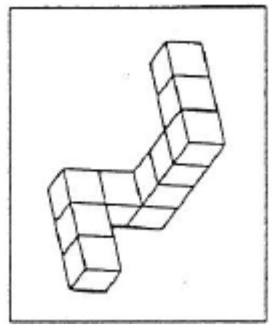
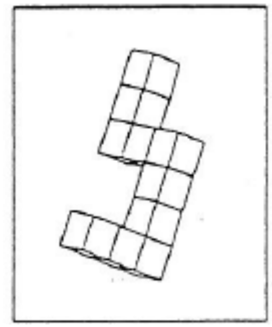
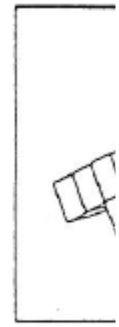
which two images are the rotated versions of the object on the left?

- 1 (1)
- 2 (2)
- 3 (3)
- 4 (4)



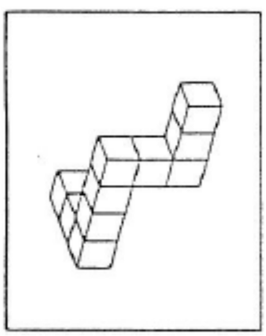
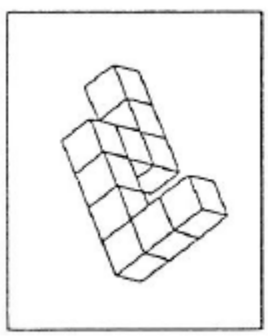
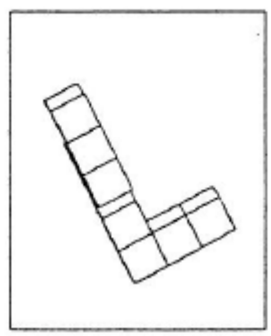
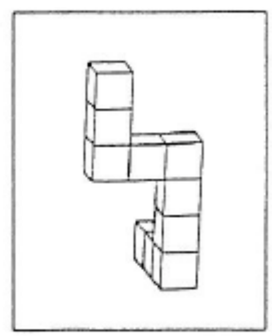
which two images are the rotated versions of the object on the left?

- 1 (1)
- 2 (2)
- 3 (3)
- 4 (4)

which two images are the rotated versions of the object on the left?

- [ ] 1 (1)
- [ ] 2 (2)
- [ ] 3 (3)
- [ ] 4 (4)

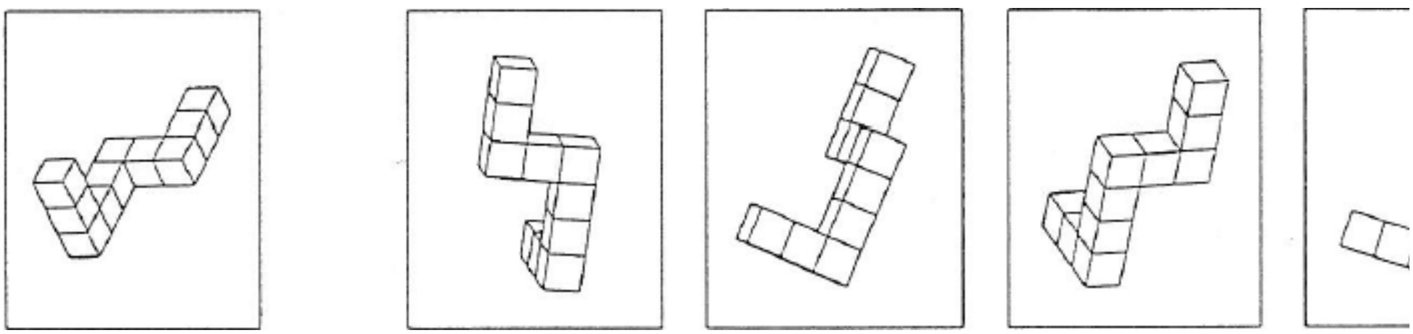
which two images are the rotated versions of the object on the left?

☐ 1 (1)

☐ 2 (2)

☐ 3 (3)

☐ 4 (4)



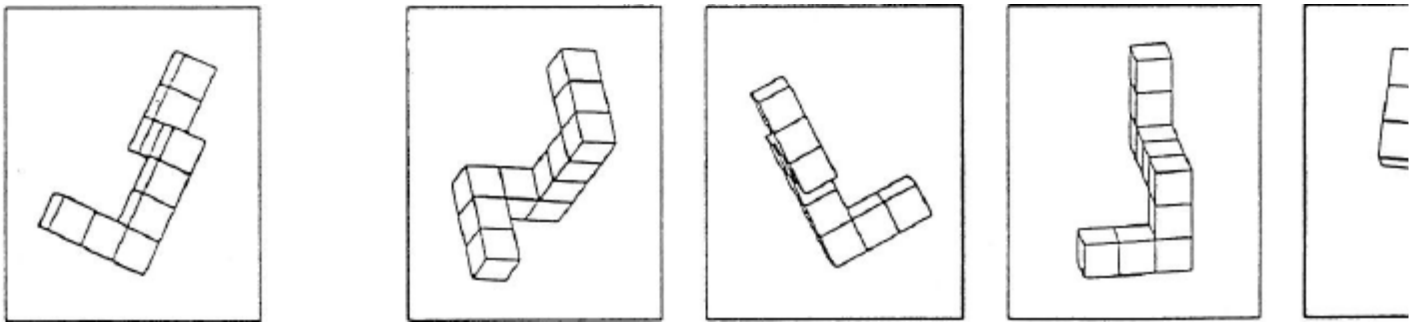
which two images are the rotated versions of the object on the left?

☐ 1 (1)

☐ 2 (2)

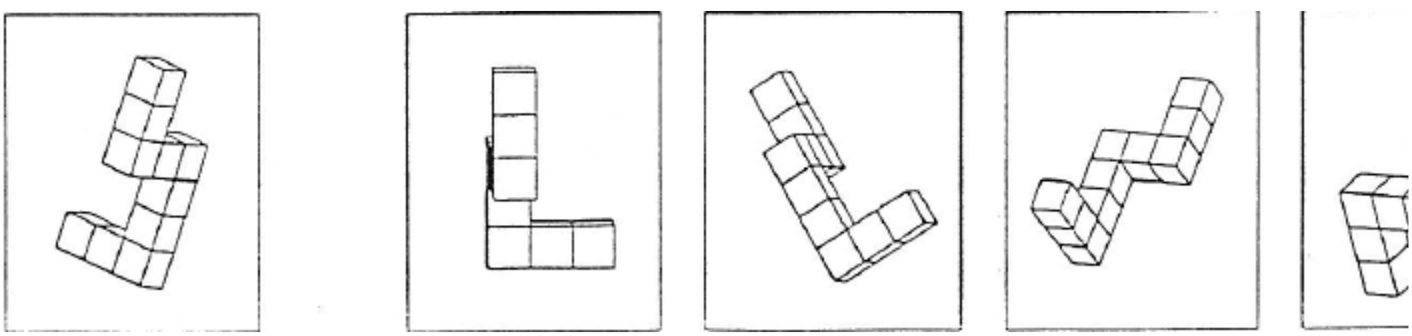
☐ 3 (3)

☐ 4 (4)



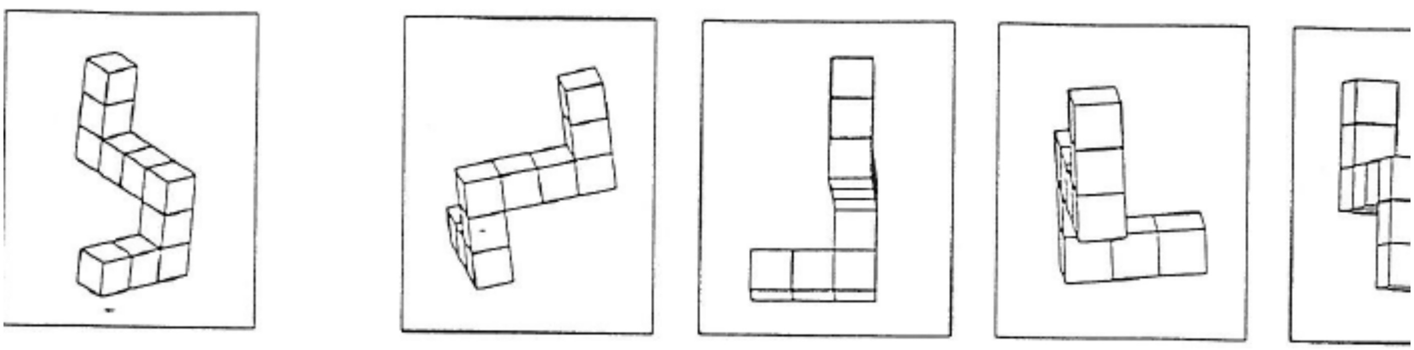
which two images are the rotated versions of the object on the left?

- 1 (1)
- 2 (2)
- 3 (3)
- 4 (4)



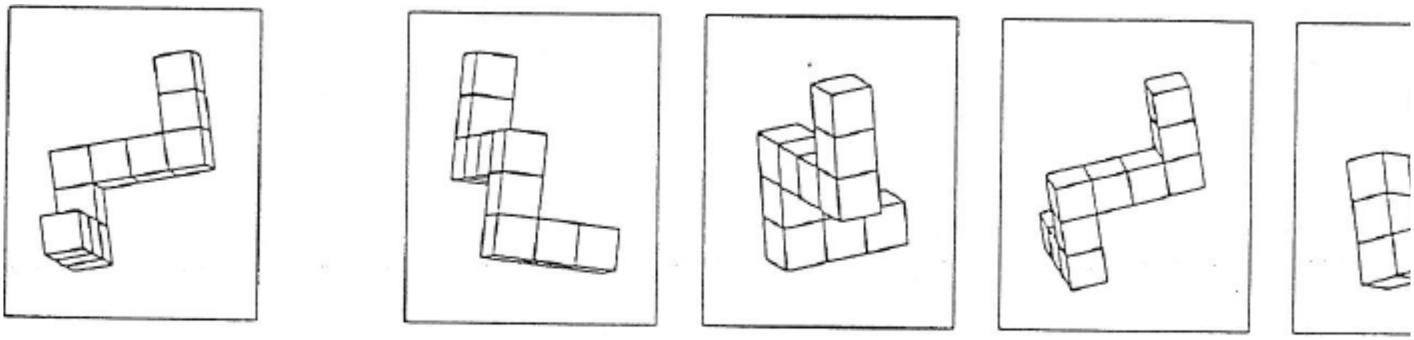
which two images are the rotated versions of the object on the left?

- 1 (1)
- 2 (2)
- 3 (3)
- 4 (4)



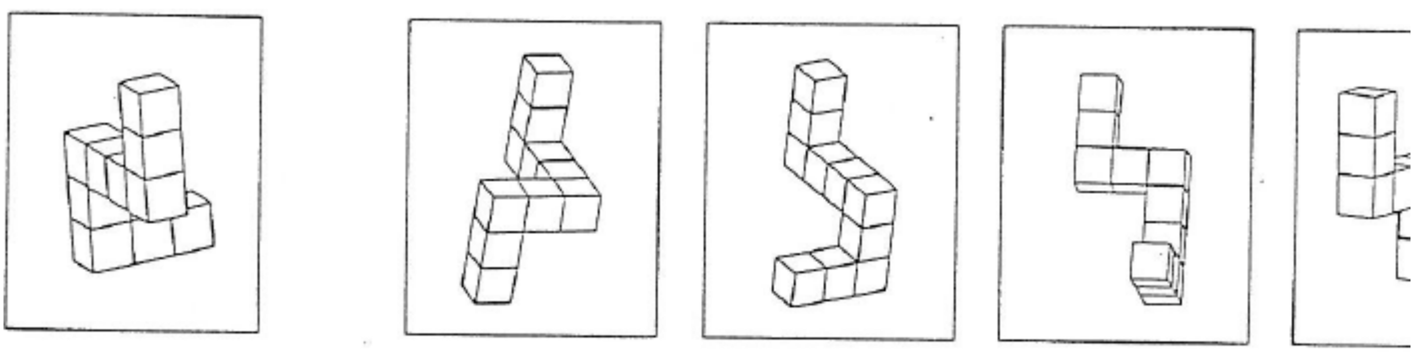
which two images are the rotated versions of the object on the left?

- 1 (1)
- 2 (2)
- 3 (3)
- 4 (4)



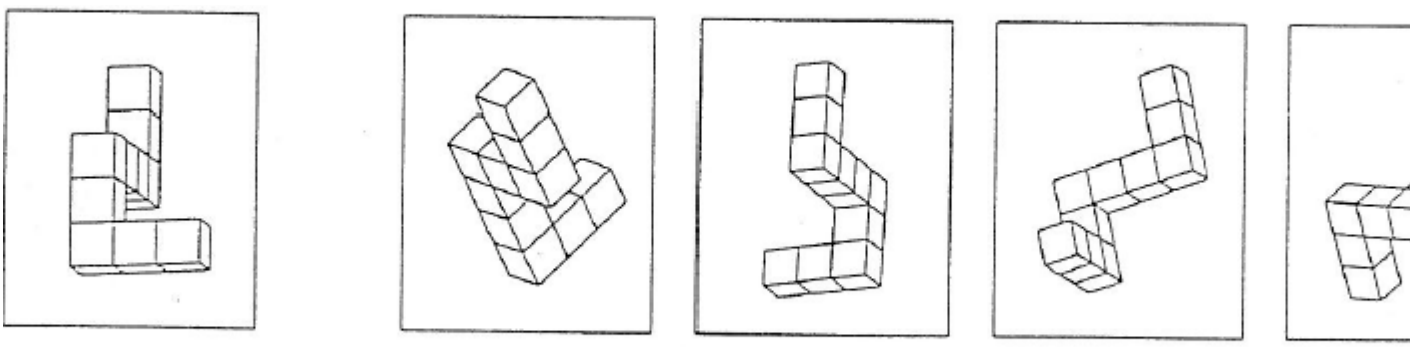
which two images are the rotated versions of the object on the left?

- 1 (1)
- 2 (2)
- 3 (3)
- 4 (4)



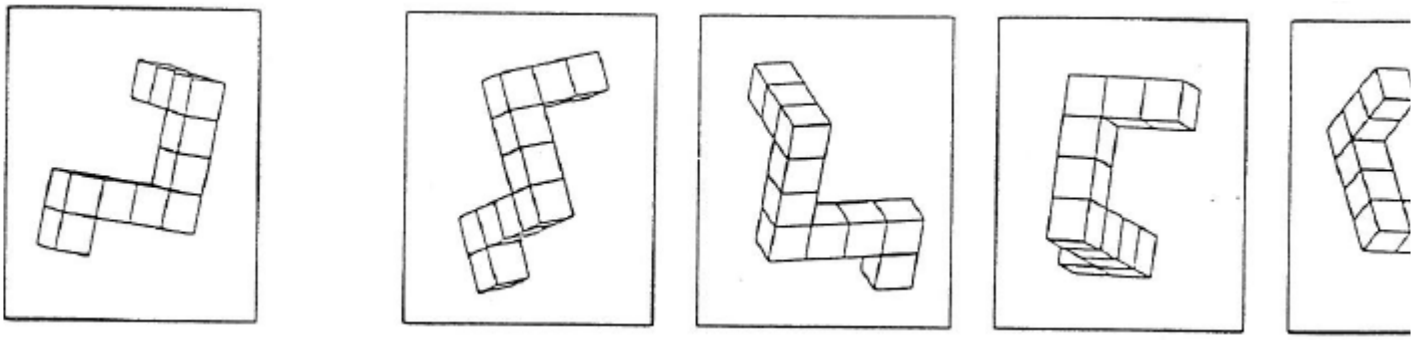
which two images are the rotated versions of the object on the left?

- 1 (1)
- 2 (2)
- 3 (3)
- 4 (4)



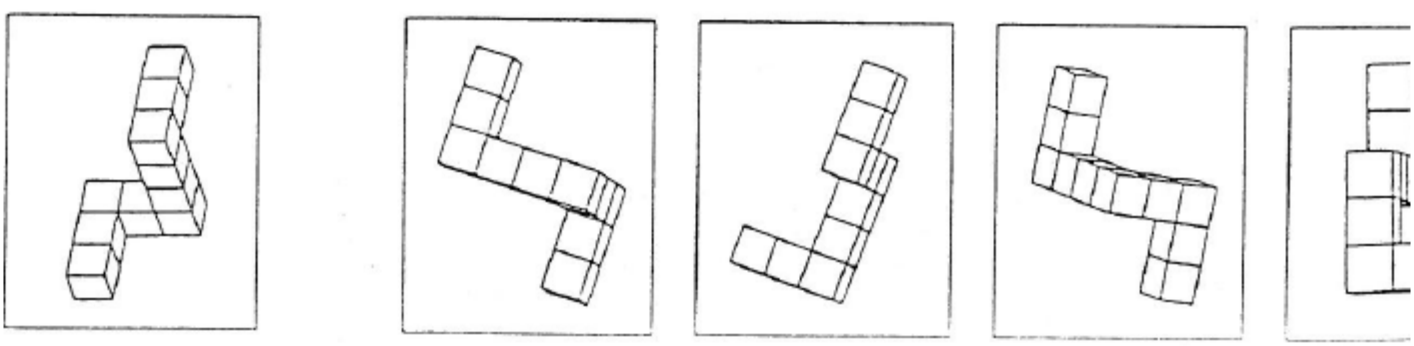
which two images are the rotated versions of the object on the left?

- 1 (1)
- 2 (2)
- 3 (3)
- 4 (4)



which two images are the rotated versions of the object on the left?

- 1 (1)
- 2 (2)
- 3 (3)
- 4 (4)



which two images are the rotated versions of the object on the left?

- [ ] 1 (1)
- [ ] 2 (2)
- [ ] 3 (3)
- [ ] 4 (4)

End of Block: MRT

8. Appendix B: Post-Experiment Survey

DCC 2018

Start of Block: Start

Type in your netid

____

Which target region did you investigate first?

○ (a) (1)

○ (b) (2)

End of Block: Start

Start of Block: Target Region (b)

1000	B	D	L	
2000				
3000	I			
4000	D	F	H	K
5000	I	L		

Do you think the above architecture is inside the target region?

◯ Yes (1)

◯ No (2)

1000	B	D	L	
2000	E	F		
3000	I			
4000	D	F	H	K
5000	B	F	L	

Do you think the above architecture is inside the target region?

◯ Yes (1)

◯ No (2)

1000	C	D	E	J	L
2000	E	F			
3000	E	I	K		
4000	F	H			
5000	L				

Do you think the above architecture is inside the target region?

- ◯ Yes (1)
- ◯ No (2)

1000	B	C
2000	C	
3000	F	L
4000	K	L
5000	E	

Do you think the above architecture is inside the target region?

- ◯ Yes (1)
- ◯ No (2)

1000	K	
2000	F	
3000	C	L
4000	J	
5000	F	I

Do you think the above architecture is inside the target region?

- ◯ Yes (1)
- ◯ No (2)

1000	D	J	L
2000			
3000			
4000	F	H	K
5000	B	L	

Do you think the above architecture is inside the target region?

- ◯ Yes (1)
- ◯ No (2)

1000	C	L	
2000	E		
3000	K		
4000	F	L	
5000	B	J	L

Do you think the above architecture is inside the target region?

◯ Yes (1)

◯ No (2)

1000	B	D	L
2000	E		
3000			
4000	F	K	
5000	D	L	

Do you think the above architecture is inside the target region?

◯ Yes (1)

◯ No (2)

1000	D	F	J	L
2000	A	E	H	K
3000	E			
4000	D			
5000	K	L		

Do you think the above architecture is inside the target region?

◯ Yes (1)

◯ No (2)

1000	A	K
2000	D	K
3000		
4000	B	
5000	H	

Do you think the above architecture is inside the target region?

◯ Yes (1)

◯ No (2)

1000	J	L		
2000				
3000	E	I		
4000	D	F	H	K
5000	B	D	L	

Do you think the above architecture is inside the target region?

◯ Yes (1)

◯ No (2)

1000	C	D	E	H	J	L
2000	E					
3000	E	I	K			
4000	D	F	H	K		
5000	B	F	L			

Do you think the above architecture is inside the target region?

◯ Yes (1)

◯ No (2)

1000	C	D	J	L
2000	E			
3000	I	K		
4000	D	F	H	K
5000	B	E	L	

Do you think the above architecture is inside the target region?

◯ Yes (1)

◯ No (2)

1000	D	K	L
2000	E		
3000	I		
4000	F	H	K
5000	B	D	L

Do you think the above architecture is inside the target region?

◯ Yes (1)

◯ No (2)

1000	D	K	L
2000			
3000	E		
4000	F	H	K
5000			

Do you think the above architecture is inside the target region?

- Yes (1)
- No (2)

1000	F	J		
2000	J			
3000	D			
4000	B	F	K	L
5000	L			

Do you think the above architecture is inside the target region?

- Yes (1)
- No (2)

1000	B	D	L	
2000				
3000				
4000	F	H	K	
5000	D	J	K	L

Do you think the above architecture is inside the target region?

- Yes (1)
- No (2)

1000	C	D	L
2000	E		
3000	I		
4000	F	H	K
5000	B	L	

Do you think the above architecture is inside the target region?

- Yes (1)
- No (2)

1000	C	D	L		
2000					
3000	I				
4000	D	E	F	H	K
5000	B	L			

Do you think the above architecture is inside the target region?

- ◯ Yes (1)
- ◯ No (2)

1000	B	D	L	
2000				
3000	K			
4000	D	F	H	K
5000	J	L		

Do you think the above architecture is inside the target region?

- ◯ Yes (1)
- ◯ No (2)

1000	B	E	J
2000	D	H	K
3000	J		
4000	E	I	
5000	F		

Do you think the above architecture is inside the target region?

◯ Yes (1)

◯ No (2)

1000	D	J	L	
2000				
3000	K			
4000	D	F	H	K
5000	B	L		

Do you think the above architecture is inside the target region?

◯ Yes (1)

◯ No (2)

1000	C	D	E	J	L
2000					
3000	I	K			
4000	D	E	F	H	K
5000	B	F	L		

Do you think the above architecture is inside the target region?

○ Yes (1)

○ No (2)

1000	B	D	L
2000			
3000			
4000	H	K	
5000	L		

Do you think the above architecture is inside the target region?

○ Yes (1)

○ No (2)

1000	B	D	
2000			
3000			
4000	F	H	K
5000	B	D	L

Do you think the above architecture is inside the target region?

- ○ Yes (1)
- ○ No (2)

End of Block: Target Region (b)

Start of Block: Target Region (b) TLX

We are not only interested in assessing your performance but also the experiences you had during the different task conditions.

We want to examine the "workload" you experienced. The factors that influence your experience of workload may come from the task itself, your feelings about your own performance, how much effort you put in, or the stress and frustration you felt.

The evaluation you are about to perform is a technique that has been developed by NASA to assess the relative importance of six factors in determining how much workload you experienced.

The definition of the six scales
Mental demand: How much metnal and perceptual activity was required (e.g. thinking, deciding, calculating, etc)? Physical demand: How much physical activity was required (e.g. pushing, pulling, turning, controlling)? Temporal demand: How much time pressure did you feel due to the rate or pace at which the tasks or task elements occurred? Performance: How successful do you think you were in accomplishing the goals of the task set by the experimenter? Effort: How hard did you have to work to accomplish your level of performance? Frustration: How insecure, discouraged, irritated, stressed and annoyyed verses secure, content, and relaxed did you feel during the task?

Extremely easy	Moderately easy	Slightly easy	Neither easy nor difficult	Slightly difficult	Moderately difficult	Extremely difficult

0 5 10 15 20 25 30 35 40 45 50 55 60 65 70 75 80 85 90 95 100

Mental Demand: How mentally demanding was the task? ()	
Physical Demand: How physically demanding was the task? ()	
Temporal Demand: How hurried or rushed was the pace of the task? ()	
Performance: How successful were you in accomplishing what you were asked to do? ()	
Effort: How hard did you have to work to accomplish your level of performance? ()	
Frustration: How insecure, discouraged, irritated, stressed, and annoyed were you? ()	

Choose the scale title that represents the more important contributor to workload for the specific task you performed in this experiment

Source of Workload

- ○ Effort (1)
- ○ Performance (2)

Source of Workload

- ○ Temporal demand (1)
- ○ Frustration (2)

Source of Workload

- ◯ Temporal demand (1)
- ◯ Effort (2)

Source of Workload

- ◯ Physical demand (1)
- ◯ Frustration (2)

Source of Workload

- ◯ Performance (1)
- ◯ Frustration (2)

Source of Workload

- ◯ Physical demand (1)
- ◯ Temporal demand (2)

Source of Workload

- ◯ Physical demand (1)
- ◯ Performance (2)

Source of Workload

○ Temporal demand (1)

○ Mental demand (2)

Source of Workload

○ Frustration (1)

○ Effort (2)

Source of Workload

○ Performance (1)

○ Mental demand (2)

Source of Workload

○ Performance (1)

○ Temporal demand (2)

Source of Workload

○ Mental demand (1)

○ Effort (2)

Source of Workload

- ◯ Mental demand (1)
- ◯ Physical demand (2)

Source of Workload

- ◯ Effort (1)
- ◯ Physical demand (2)

Source of Workload

- ◯ Frustration (1)
- ◯ Mental demand (2)

Page Break

End of Block: Target Region (b) TLX

Start of Block: Target Region (b) UEQ

Please assess your experience now by ticking one circle per line.

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)	
Annoying	○	○	○	○	○	○	○	Enjoyable
Not Understandable	○	○	○	○	○	○	○	Understandable
Creative	○	○	○	○	○	○	○	Dull
Easy to Learn	○	○	○	○	○	○	○	Difficult to Learn
Valuable	○	○	○	○	○	○	○	Inferior
Boring	○	○	○	○	○	○	○	Exciting
Not Interesting	○	○	○	○	○	○	○	Interesting
Unpredictable	○	○	○	○	○	○	○	Predictable
Fast	○	○	○	○	○	○	○	Slow
Inventive	○	○	○	○	○	○	○	Conventional
Obstruvtive	○	○	○	○	○	○	○	Supportive
Good	○	○	○	○	○	○	○	Bad
Complicated	○	○	○	○	○	○	○	Easy
Unlikable	○	○	○	○	○	○	○	Pleasing
Usual	○	○	○	○	○	○	○	Leading Edge
Unpleasant	○	○	○	○	○	○	○	Pleasant

Secure	○	○	○	○	○	○	○	Not Secure
Motivating	○	○	○	○	○	○	○	Demotivating
Meets Expectations	○	○	○	○	○	○	○	Does Not Meet Expectations
Inefficient	○	○	○	○	○	○	○	Efficient
Clear	○	○	○	○	○	○	○	Confusing
Impractical	○	○	○	○	○	○	○	Practical
Organized	○	○	○	○	○	○	○	Cluttered
Attractive	○	○	○	○	○	○	○	Unattractive
Friendly	○	○	○	○	○	○	○	Unfriendly
Conservative	○	○	○	○	○	○	○	Innovative

End of Block: Target Region (b) UEQ

Start of Block: Pause

Please stop here. Continue to the next section after you have completed the next task.

End of Block: Pause

Start of Block: Target Region (a)

1000	G			
2000	C	D		
3000	A	H	J	L
4000	D	H	L	
5000				

Do you think the above architecture is inside the target region?

- Yes (1)
- No (2)

1000	H	L
2000	K	
3000		
4000		
5000	H	

Do you think the above architecture is inside the target region?

- Yes (1)
- No (2)

1000		
2000		
3000	A	L
4000	C	G
5000	H	

Do you think the above architecture is inside the target region?

- Yes (1)
- No (2)

1000				
2000				
3000	A	H	J	L
4000	D	L		
5000				

Do you think the above architecture is inside the target region?

- Yes (1)
- No (2)

1000	E	H			
2000	D	L			
3000	A	H	J	L	
4000	B	D	F	G	L
5000					

Do you think the above architecture is inside the target region?

◯ Yes (1)

◯ No (2)

1000	D	
2000	D	I
3000	E	L
4000	H	L
5000	J	

Do you think the above architecture is inside the target region?

◯ Yes (1)

◯ No (2)

1000			
2000	D	H	
3000	A	J	L
4000	C	D	L
5000			

Do you think the above architecture is inside the target region?

- Yes (1)
- No (2)

1000				
2000	D	H		
3000	L			
4000	C	D	J	L
5000				

Do you think the above architecture is inside the target region?

- Yes (1)
- No (2)

1000			
2000	D		
3000	A	H	L
4000	D	J	L
5000			

Do you think the above architecture is inside the target region?

- ◯ Yes (1)
- ◯ No (2)

1000	D	H	L
2000	E	J	
3000	B	D	L
4000	D	L	
5000			

Do you think the above architecture is inside the target region?

- ◯ Yes (1)
- ◯ No (2)

1000	E			
2000	C	D	L	
3000	A	M	J	L
4000	D	H	L	
5000	G			

Do you think the above architecture is inside the target region?

- Yes (1)
- No (2)

1000			
2000	D		
3000	H	J	L
4000	C	D	L
5000			

Do you think the above architecture is inside the target region?

- Yes (1)
- No (2)

1000		
2000		
3000	J	L
4000	B	H
5000	A	L

Do you think the above architecture is inside the target region?

- ◯ Yes (1)
- ◯ No (2)

1000			
2000	H		
3000	A	J	L
4000	C	D	L
5000			

Do you think the above architecture is inside the target region?

- ◯ Yes (1)
- ◯ No (2)

1000					
2000	D	H			
3000	A	J	L		
4000	C	D	L		
5000	E				

Do you think the above architecture is inside the target region?

- ◯ Yes (1)
- ◯ No (2)

1000					
2000	D	L			
3000	A	E	H	J	L
4000	C	D	L		
5000	G				

Do you think the above architecture is inside the target region?

- ◯ Yes (1)
- ◯ No (2)

1000	D	
2000		
3000	L	
4000	H	
5000	K	L

Do you think the above architecture is inside the target region?

- ◯ Yes (1)
- ◯ No (2)

1000	I			
2000	C	H		
3000	C	G	J	L
4000	A	E	L	
5000	I			

Do you think the above architecture is inside the target region?

- ◯ Yes (1)
- ◯ No (2)

1000	E			
2000	B	C	D	L
3000	A	H	J	L
4000	B	D		
5000				

Do you think the above architecture is inside the target region?

- ◯ Yes (1)
- ◯ No (2)

1000	E			
2000	D	L		
3000	A	H	J	L
4000	B	D		
5000				

Do you think the above architecture is inside the target region?

- ◯ Yes (1)
- ◯ No (2)

1000					
2000	D	L			
3000	H	J	L		
4000	C	D	L		
5000					

Do you think the above architecture is inside the target region?

- ◯ Yes (1)
- ◯ No (2)

1000	E				
2000	B				
3000	A	B	H	J	L
4000	C	D	L		
5000					

Do you think the above architecture is inside the target region?

- ◯ Yes (1)
- ◯ No (2)

1000			
2000	D		
3000	A	H	L
4000	D	J	L
5000	C		

Do you think the above architecture is inside the target region?

- ◯ Yes (1)
- ◯ No (2)

1000	I		
2000	A	J	L
3000	K	L	
4000	B	L	
5000	J		

Do you think the above architecture is inside the target region?

- ◯ Yes (1)
- ◯ No (2)

1000	L	
2000	A	
3000	H	L
4000	B	D
5000		

Do you think the above architecture is inside the target region?

- ◯ Yes (1)
- ◯ No (2)

End of Block: Target Region (a)

Start of Block: Target Region (a) TLX

We are not only interested in assessing your performance but also the experiences you had during the different task conditions.

We want to examine the "workload" you experienced. The factors that influence your experience of workload may come from the task itself, your feelings about your own performance, how much effort you put in, or the stress and frustration you felt.

The evaluation you are about to perform is a technique that has been developed by NASA to assess the relative importance of six factors in determining how much workload you experienced.

The definition of the six scales

Mental demand: How much metnal and perceptual activity was required (e.g. thinking, deciding, calculating, etc)? Physical demand: How much physical activity was required (e.g. pushing, pulling, turning, controlling)? Temporal demand: How much time pressure did you feel due to the rate or pace at which the tasks or task elements occurred? Performance: How successful do you think you were in accomplishing the goals of the task set by the experimenter? Effort: How hard did you have to work to accomplish your level of performance? Frustration: How insecure, discouraged, irritated, stressed and annoyyed verses secure, content, and relaxed did you feel during the task?

	Extremely easy	Moderately easy	Slightly easy	Neither easy nor difficult	Slightly difficult	Moderately difficult	Extremely difficult

0 5 101520253035404550556065707580859095100

Mental Demand: How mentally demanding was the task? ()	
Physical Demand: How physically demanding was the task? ()	
Temporal Demand: How hurried or rushed was the pace of the task? ()	
Performance: How successful were you in accomplishing what you were asked to do? ()	
Effort: How hard did you have to work to accomplish your level of performance? ()	
Frustration: How insecure, discouraged, irritated, stressed, and annoyed were you? ()	

Choose the scale title that represents the more important contributor to workload for the specific task you performed in this experiment

---

Source of Workload

- ○ Effort (1)
- ○ Performance (2)

Source of Workload

- ○ Temporal demand (1)
- ○ Frustration (2)

Source of Workload

- ○ Temporal demand (1)
- ○ Effort (2)

Source of Workload

- ○ Physical demand (1)
- ○ Frustration (2)

Source of Workload

- ○ Performance (1)
- ○ Frustration (2)

Source of Workload

- Physical demand (1)
- Temporal demand (2)

Source of Workload

- Physical demand (1)
- Performance (2)

Source of Workload

- Temporal demand (1)
- Mental demand (2)

Source of Workload

- Frustration (1)
- Effort (2)

Source of Workload

- Performance (1)
- Mental demand (2)

Source of Workload

- ◯ Performance (1)
- ◯ Temporal demand (2)

Source of Workload

- ◯ Mental demand (1)
- ◯ Effort (2)

Source of Workload

- ◯ Mental demand (1)
- ◯ Physical demand (2)

Source of Workload

- ◯ Effort (1)
- ◯ Physical demand (2)

Source of Workload

- ◯ Frustration (1)
- ◯ Mental demand (2)

Page Break

End of Block: Target Region (a) TLX

Start of Block: Target Region (a) UEQ

Please assess your experience now by ticking one circle per line.

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)	
Annoying	○	○	○	○	○	○	○	Enjoyable
Not Understandable	○	○	○	○	○	○	○	Understandable
Creative	○	○	○	○	○	○	○	Dull
Easy to Learn	○	○	○	○	○	○	○	Difficult to Learn
Valuable	○	○	○	○	○	○	○	Inferior
Boring	○	○	○	○	○	○	○	Exciting
Not Interesting	○	○	○	○	○	○	○	Interesting
Unpredictable	○	○	○	○	○	○	○	Predictable
Fast	○	○	○	○	○	○	○	Slow
Inventive	○	○	○	○	○	○	○	Conventional
Obstruvtive	○	○	○	○	○	○	○	Supportive
Good	○	○	○	○	○	○	○	Bad
Complicated	○	○	○	○	○	○	○	Easy
Unlikable	○	○	○	○	○	○	○	Pleasing
Usual	○	○	○	○	○	○	○	Leading Edge
Unpleasant	○	○	○	○	○	○	○	Pleasant

Secure	○	○	○	○	○	○	○	Not Secure
Motivating	○	○	○	○	○	○	○	Demotivating
Meets Expectations	○	○	○	○	○	○	○	Does Not Meet Expectations
Inefficient	○	○	○	○	○	○	○	Efficient
Clear	○	○	○	○	○	○	○	Confusing
Impractical	○	○	○	○	○	○	○	Practical
Organized	○	○	○	○	○	○	○	Cluttered
Attractive	○	○	○	○	○	○	○	Unattractive
Friendly	○	○	○	○	○	○	○	Unfriendly
Conservative	○	○	○	○	○	○	○	Innovative

End of Block: Target Region (a) UEQ

Start of Block: Demographic

Type in the key number that is displayed on the data analysis page

____

What is your age?

____

What is your gender?

- ○ Male (1)
- ○ Female (2)

What best describes your level of education?

- ○ Less than high school (1)
- ○ High school graduate (2)
- ○ Some college (3)
- ○ 2 year degree (4)
- ○ 4 year degree (5)
- ○ Professional degree (6)
- ○ Doctorate (7)

What best describes your undergraduate major?

- ◯ Aerospace Engineering (1)
- ◯ Biological / Agricultural / Biomedical Engineering (2)
- ◯ Chemical Engineering (3)
- ◯ Civil / Environmental Engineering (4)
- ◯ Computer Science / Information Science (5)
- ◯ Electrical Engineering (6)
- ◯ Industrial / Systems Engineering (7)
- ◯ Mechanical Engineering (8)
- ◯ Mathematics / Statistics (9)
- ◯ Physics (10)
- ◯ Chemistry (11)
- ◯ Biological Science (12)
- ◯ Other (13)

Do you have prior experience or education in satellite system design?

- ◯ Yes (1)
- ◯ No (2)

Did you understand the concepts and the task you had to perform? Please comment below.

____

____

____

____

____

Did you use all the tools that were provided? Briefly explain the strategy you used to extract useful patterns from the data.

____

____

____

____

____

How did you feel about the level of difficulty of the tasks?

____

____

____

____

____

End of Block: Demographic