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Assignment 2

2-5.

Introduction: This exercise stated to conduct an experiment on gestural input, human performance, and human error. It instructed the use of the `GraffitiExperiment` software provided on the course book's website. The exercise also stated to recruit around 10 participants, which would then be divided into two groups that would use different input methods. The first group would use a mouse and the second group would use the computer touchpad. This exercise is designed to test different input methods between subjects related to gestural input, human performance, and human error rates. This is important within human-computer interaction (HCI) because it involves users inputting into a machine. Because of this, it is important to find an input method that is easy to learn, efficient, and keeps errors at a minimum. Testing these two different input methods will give data that will be able to find the most efficient method. I suspect that the mouse will have a faster entry speed, less keystroke per character, and a lower error rate.

Methodology: The specifications for this exercise were generally clear. I downloaded and unzipped the `GraffitiExperiment` that was specified above. I was then able to set up and run the jar file and experiment on my Macbook Air. The program would prompt participants to draw a pattern/gesture which represented a letter of the alphabet, completing all 26 letters in order, which can be seen in Figure 1. The experiment specifications also stated that participants may correct errors using the `Backspace` gesture (←); they should not attempt to correct a symbol more than three times. Each user was tested 10 times for their assigned input method. All incorrectly drawn letters represent an error and the software recorded the correct letters, errors, keystrokes per character (KSPC), time, and words per minute (WPM). (As specified by the exercise, a "keystroke," in this instance, is a gesture stroke.) Per the experiment instructions, I recruited 10 participants. The first group of 5 participants used a magic mouse, condition 1 (CO1), (Figure 2) and the second group, which also consisted of 5 participants, used the laptop's touchpad, condition 2 (CO2) (Figure 3). After collecting the samples and data, the data was derived using Google Sheets.

Figures/Tables:

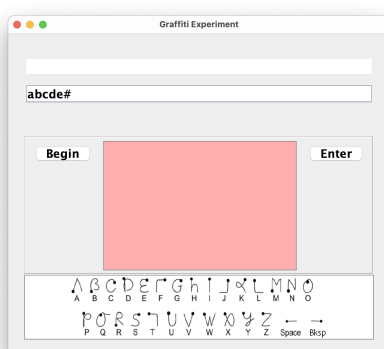

Figure 1: Graffiti Experiment Interface

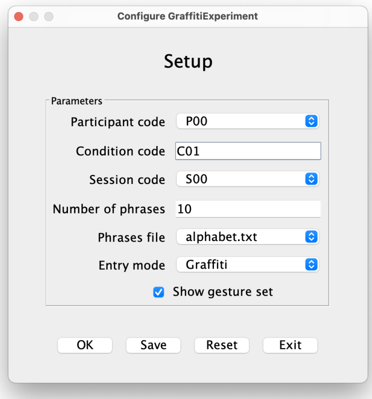

Figure 2: GraffitiExperiment Setup with Condition 1

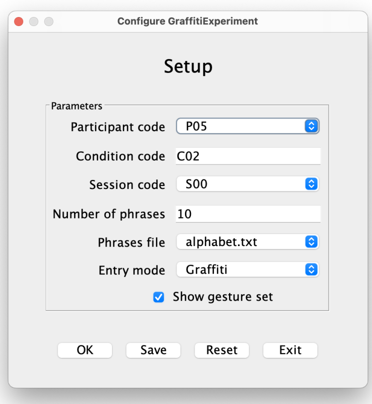

Figure 3: GraffitiExperiment Setup with Condition 2

Table 1: Graffiti Experiment Average Results per Participant

Participant	Input Device	Average Entry Speed (WPM)	Average Error Rate (%)	Average Keystrokes Per Char (KSPC)
00	Magic Mouse	13.892	37.308	1.000
01	Magic Mouse	4.960	12.821	1.100
02	Magic Mouse	8.695	41.016	1.015
03	Magic Mouse	8.172	34.374	1.083
04	Magic Mouse	8.909	35.639	1.015
05	Laptop Touchpad	3.878	14.133	1.109
06	Laptop Touchpad	10.339	29.615	1.097
07	Laptop Touchpad	4.249	0.427	1.440
08	Laptop Touchpad	7.606	14.557	1.043
09	Laptop Touchpad	8.825	33.726	1.116

Table 2: Graffiti Experiment Average Results per Input Device

Input Device	Average Entry Speed (WPM)	Average Error Rate (%)	Average Keystrokes Per Char (KSPC)
Magic Mouse	8.926	32.231	1.043
Laptop Touchpad	6.979	18.492	1.161

Results: The data collected on each participant can be seen in Table 1 and Table 2. The statistics that are seen in Table 1 are the average for each property (i.e. average entry speed (WPM), etc.) broken out by participants. Additionally, the statistics that can be seen in Table 2 are the average for each property per the input device. One of the important values collected was the error rate. The error rate is nearly double for the Magic Mouse compared to the Laptop Touchpad, further information can be read in the conclusion below (Table 2). Although I did not include the individual participant data, due to the tables being so large, I did not see an overall learned affect given that each participant did 10 iterations of the experiment. The graphical representation of the data gave no new insights, which is why it was also not included in the figures.

Conclusion: This experiment gave a correlation between entry speed (WPM), error rate, and average keystrokes per character (KSPC) given two groups of participants. As mentioned above my initial hypothesis and suspicions were that the mouse will have a faster entry speed, a lower error rate and less keystrokes per character. Most of my assumptions were correct. First, the mouse average entry speed was 8.926 WPM while the touchpad average entry speed was 6.979; this means that I was correct in assuming that the mouse would have a faster entry speed (Table 2). Second, the average error rate for the mouse was 32.231% and while it was 18.492% for the touchpad; this means that my assumption was incorrect that the mouse users would have a higher accuracy (Table 2). During the experiment, I noticed that although mouse users became increasingly irritated with the method input while they went through all 10 iterations, I also noticed or heard comments from mouse users that the mouse lagged slightly and was uncomfortable to use. The latency and difficulty of use of the specific mouse may be why the accuracy was inaccurate about half as often as the touchpad. Lastly, the average KSPC for the Magic Mouse was 1.043 and 1.161 for the laptop touchpad; this means that the initial assumption that the mouse would have less keystrokes per character was also correct (Table 2). Because of these results, I would state that the touchpad is a better input to users for drawing keystrokes for the alphabet in a given window. This said, I would like to state that the touchpad is better when compared to the Magic Mouse in particular. It would be very interesting to see another study comparing various mouse devices compared to a touchpad.

6-3.

Introduction: This exercise gives data relating to 10 participants divided into 2 groups, 5 gamers and 5 non-games were asked to perform 5 object-manipulation tasks. The task completion times were logged and given in a tabular format which can be seen in Table 3. The exercise then states to perform an analysis of variance (ANOVA) test on the data to determine if there is an effect of participant background (gamer versus non-gamer) on the task completion time. It also states to investigate whether learning occurred over the tasks and whether the learning progress, if any, was the same for both groups of participants. The report of the findings will include a chart to illustrate the findings. The exercise is meant to allow familiarity with ANOVA testing. This exercise in particular had a single-factor test that focused on the independent variable of gamers vs non-gamers. Because this experiment is designed as a between-subject study, an ANOVA test will be sufficient.

Methodology: Although the exact specifications and information for running the ANOVA test for this exercise were very unclear I was eventually able to run the test. First, I typed the data into Google Sheets and downloaded it as a comma separated value (CSV) (Table 3). Then I downloaded `GoStats` from the courses textbook website. I then updated the CSV file to include headers and uploaded the saved CSV into `GoStats` to analyze the data and perform the ANOVA test. The software recognized there were 10 participants; there were 5 within-subject factors and 2 between subject factors based on the provided headers in the CSV files (Figure 4). I also decided to take the data that was entered into Google Sheets and create graphs to view any potential learning affects across non-gamers and gamers (Figure 5 and Figure 6).

Figures/Tables:

Table 3: Provided Data Table in Exercise 6-3

Participant	Task Completion Time (s)					Background
	T1	T2	T3	T4	T5	
P1	23	21	16	17	15	Non-gamer
P2	24	21	20	17	14	Non-gamer
P3	24	20	21	15	13	Non-gamer
P4	26	21	20	17	16	Non-gamer
P5	17	18	20	15	14	Non-gamer
P6	19	16	15	14	15	Gamer
P7	20	16	15	13	14	Gamer
P8	16	16	14	13	11	Gamer
P9	15	15	12	14	12	Gamer
P10	17	16	13	14	12	Gamer

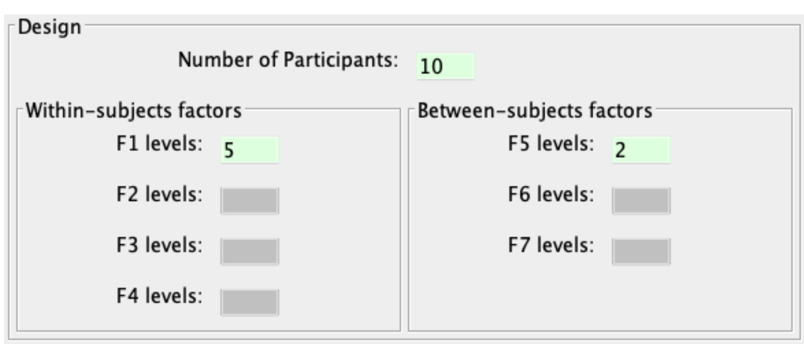

Figure 4: GoStats ANOVA Data Design for Exercise 6-4

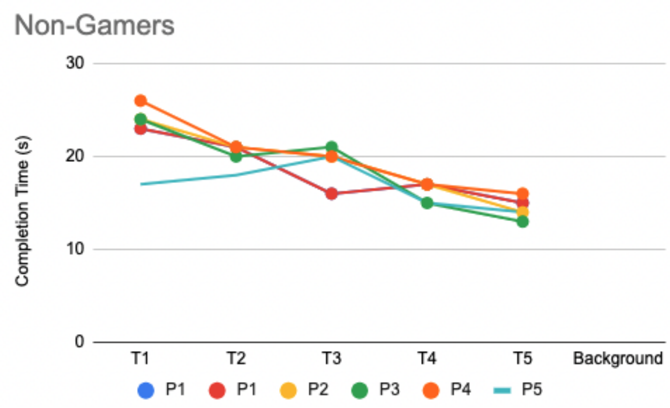

Figure 5: Learned Affect for Non-Gamers

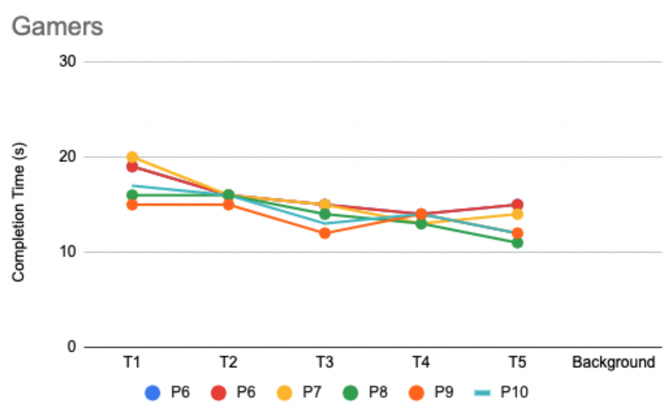

Figure 6: Learned Affect for Gamers

Table 4: ANOVA Table for Completion Time

Effect	df	SS	MS	F	p
Group	1	192.080	192.080	32.667	0.0004
Participant(Group)	8	47.040	5.880		
Task Time	4	260.920	65.230	30.446	0.0000
Task Time_x_Group	4	30.920	7.730	3.608	0.0155
Task Time_x_P(group)	32	68.560	2.143		

Results: Figure 5 and Figure 6 display the task compilation time for each task (i.e. T1) for each participant over the duration of the experiment. The scales were standardized for both graphs so the slope was standardized and decreased bias in visually comparing the two datasets. The results show that the learned affect in the non-gamer group was more pronounced than the gamer group. This can be deduced because the non-gamer group began with longer completion times in the first iteration and as they continued with the experiment it continued to decrease, implying the participants were learning through the trial periods (Figure 5). Table 4 is the ANOVA data table from the GoStats software. The resulting p-value is 0.015 which means that there is only a 1.5% chance that the data obtained was due to the null hypothesis; this also means that there is a 98.5% certainty that the outcome of gamers are better at manipulating 3D objects than the non-gamers that were observed.

Conclusion: Based on the data given in this exercise, there was significant evidence, with a p-value of 0.015 that there was an effect of participant background (non-gamer vs gamer) against task completion time (Table 4). The group of gamers were faster at completing the tasks given compared to the non-gamers. This confirms the given hypothesis that participant backgrounds would indicate better abilities at manipulating objects in a 3D environment. It is likely that this hypothesis formed because the researchers had an idea that gamers have some muscle memory or intuition from using controllers, of some form, and the hand-eye coordination from their games. Regardless if it's from a game or another real world application, repeated completion of tasks can condition a participant to excel in other tasks that are similar to those they have been conditioned with. This can be observed over the experiment duration as we can see as we see the task completion times decrease for each group (Figure 5 and Figure 6). These learned affects help both groups of participants. This may be because non-gamers, although they may have no experience, they learn it while performing the tasks through the iterations of the experiment. Non-gamers are learning and improving their understanding and ability to manipulate 3D objects. On the other hand, gamers may already be comfortable and have experience with controllers and displays before the experiment. Thus, gamers have a smaller learning affect with manipulated 3D objects, but they already have the previous knowledge before beginning the experiment.

6-4.

Introduction: This exercise gives data relating to 12 participants to see if interactions with touchscreen phones were improved using the flick gesture and whether the improvement, if any, was related to a one-handed versus a two-handed interaction (Table 5). The 12 participants were divided into 2 groups of 6, counterbalancing the one-handed versus two-handed conditions, making this study a within-subject design. Participants were asked to do a variety of map-locating tasks that were equally difficult. For each task, participants were given a starting location and were required to navigate through the map image in order to find the final location using finger gestures. The study made sure that the map and locations were familiar to participants in order to avoid difficult visual searches in the task. The system was also configured to have a drag-only mode (flick disabled) and a drag + flick mode. The exercise then stated to perform an analysis of variance (ANOVA) test on the data to determine if there is an effect of hand use (one-handed versus two-handed) or interaction method (drag-only versus drag + flick) on the completion time of the map-locating task. This exercise is meant to allow familiarity with ANOVA testing. This is important because ANOVA testing is extremely helpful to test multiple variables. In human computer interaction specifically, it can help determine if various factors have an effect on efficiency for users interacting with various machines with similar features, like touchscreens.

Methodology: This exercise did not have any specifications or information for running the ANOVA test yet I was able to run the analysis. First, I typed the data into Google Sheets and downloaded it as a comma separated value (CSV) (Table 4). I then updated the CSV file to include headers and uploaded the saved CSV into `GoStats` to analyze the data and perform the ANOVA test. With the provided headers in the CSV file, the software recognized there were 12 participants, 4 within-subject factors: 2 grouped by handedness (one-handed, two-handed) and another 2 grouped by interaction (drag, drag-flick) (Figure 7).

Figures/Tables:

Table 5: Provided Data Table in Exercise 6-4

Participant	Task Completion Time (s)				Group
	One-handed		Two-handed		
	Drag-only	Drag+flick	Drag-only	Drag+flick	
P1	12	11	7	6	G1
P2	11	7	6	8	G1
P3	9	8	8	7	G1
P4	9	9	7	6	G1
P5	13	5	6	5	G1
P6	6	6	5	9	G1
P7	7	7	8	8	G2
P8	9	8	9	5	G2
P9	8	8	9	7	G2
P10	7	8	9	5	G2
P11	11	10	8	11	G2
P12	12	8	8	11	G2

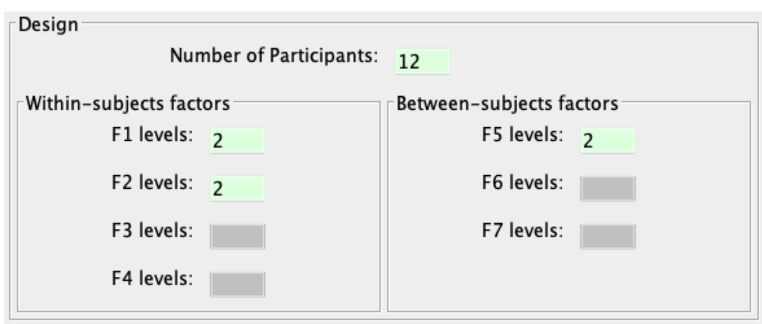

Figure 7: GoStats ANOVA Data Design for Exercise 6-4

Table 8: ANOVA Table for Completion Time

Effect	df	SS	MS	F	p
Group	1	4.687	4.687	1.106	0.3177
Participant(group)	10	42.375	4.238		
Handedness	1	20.021	20.021	7.995	0.0179
Handedness_x_Group	1	9.187	9.187	3.669	0.0844
Handedness_x_P(group)	10	25.042	2.504		
Interaction	1	9.188	9.188	3.182	0.1048
Interaction_x_Group	1	0.187	0.187	0.065	0.8040
Interaction_x_P(group)	10	28.875	2.888		
Handedness_x_Interaction	1	6.021	6.021	1.485	0.2509
Handedness_x_Interaction_x_G	1	4.688	4.688	1.156	0.3075
Handedness_x_Interaction_x_P	10	40.542	4.054		

Results: Table 8 shows the ANOVA data and analysis table from the `GoStats` software. The analysis gave several interesting insights. First, for interaction (drag, drag + flick) the p-value is 0.1048 which means that there is a 10.48% chance that the given data was due to the null hypothesis. Second, the p-value for the improvement given the interaction compared with the handedness interaction (one-handed, two-handed) is 0.2509 which means there is a 25.09% chance that the data was due to null hypothesis that there is not an improvement between gesture and handedness (Table 8).

Conclusion: Given the data in this exercise, there was not significant evidence, with a p-value of 0.1048 for gestures, that there was an effect of gestures (drag, drag+flick) against task completion time (Table 4). Additionally, there was not significant evidence, with a p-value of 0.2509, that there was an effect of hand use and interaction method on task completion time (Table 4). Not significant evidence suggests that the null hypothesis would be rejected. The null hypothesis in this case is that there is an effect of hand use or interaction method on task completion time for the stated map-locating task above. Overall, this means that gestures likely do not have an effect on task completion time and it is also not likely improved further with the handedness interaction.