DIFFERENCES IN LEARNING FROM COMPLEX VERSUS SIMPLE VISUAL INTERFACES WHEN OPERATING A MODEL EXCAVATOR

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Abstract: The goal of this study was to test two visual co-robot interfaces (one simple and one more complex) and their effectiveness in teaching a novice participant to operate a complex machine at a later date without assistance. Participants (N = 113) were randomly assigned to one of three groups (one with a basic user interface, one with a more complex guidance interface, and one without an interface) to test the teaching ability of the co-robot in training the user to perform a task with a remote-controlled excavator. Each group was asked to load dirt from a bin into a small model dump truck (in scale with the excavator) with the help of the robot instructor and were asked to return a few days later to complete the task again without the robot instructor. Trials were monitored for completion time and errors and compared to those of an expert operator. The result was that the simple interface was slightly more effective than the more complex version at teaching humans a complicated task. This suggests that novices may learn better and retain more information when given basic feedback (using operant conditioning principles) and less guidance from robot teachers. As robots are increasingly used to help humans learn skills, industries may benefit from simpler guided instructions rather than more complex versions. Such changes in training may result in improved situational awareness and increased safety in the workplace.

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CHAPTER I

INTRODUCTION

Robots are becoming increasingly commonplace in industries worldwide and are completing complex tasks once thought to be unique to humans. In addition to being used in manufacturing, some robots, often referred to as co-robots or cobots, have been developed to work in collaboration with humans in various industries to perform physical tasks (Cherubini, Passama, Crosnier, Lasnier, & Fraisse, 2016). The future of this industry, however, is becoming increasingly dependent upon the use of computerized equipment, autonomous and semiautonomous machinery, and co-robot training equipment that utilizes computer-based interactions in order for operators to train and use the machinery. Due to the shared responsibilities these co-robots have with their human partners, they cannot fully replace every human occupation. Despite their limitations, however, there are unique ways in which co-robots might assist in instructing novices and students to learn complex tasks.

Most studies involving human and robot learning focus on how robots learn from humans (Thomaz & Breazeal, 2008; Kaipa, Bongard, & Meltzoff, 2010; Cantrell, Schermerhorn, & Scheutz, 2011; Chatzis, Korkinof, &Demiris, 2012; Grand, Mostafaoui, Hasnain, and Gaussier; 2014; Tangkaratt, Morimoto, & Sugiyama, 2016) and how humans can teach robots (Kartoun, Stern & Edan, 2010; Koenig, Takayama, Mataric, 2010; Ferreira & Lefevre, 2015; Xia & El Kamel, 2016) even while simultaneously performing the same physical task (Gavish, Gutierrez, Webel, & Rodriguez, 2011; Ikemoto, Ben Amor, Minato, Jung, & Ishiguro, 2012; Garrido, Yu & Soria, 2015; Kupcsik, Hsu, & Lee, 2016). Most of these studies focus on demonstration as the primary teaching method and fail to apply principals of learning theory, positive reinforcement, or operant conditioning with regards to humans learning complex tasks from robots.

Development and research into effective training models that involve visual teaching and guidance interfaces needs to account for how humans learn under these conditions. With regards to interactive experiences, simple interfaces help reduce stimulant load during learning which suggests a basic interface would promote better retention of acquired skills (Paas, Tuovinen, Tabbers, & Van Gerven, 2010). Furthermore, studies show that videos are effective at teaching tasks and problem solving strategies in both children and adults (Chen & Siegler, 2013; Flynn & Whiten, 2013) which further supports its use in a training model. Additionally, the use of limited guidance or feedback, especially in the early training of novices, can also increase learning (Van Merrienboer, Kester, & Paas, 2006). All of this suggests that video interfaces may prove useful for training novices with co-robots and that novices may have better retention if they are guided with a simple versus complex interface.

Previous experience may also play an important role in the development of co-robot teaching interfaces. For example, Individuals with experience and exposure to comparable environments have a much easier time learning similar material (Williams & Lombrozo, 2013) and handling distractions than those without prior experience (Petzoldt, Bar, Ihle, &Krems, 2011). This is especially critical considering the potential danger on construction sites and further highlights the importance of experience in establishing individual backgrounds in order to predict the individual trainees' behavior.

This study was designed to look at operant conditioning and visual reinforcement in the robot-human interaction, but, more importantly, to determine which version of the visual feedback would result in retention of information and learned skills. Operant conditioning pertains to subjects' conscious behavioral responses to an environment where as classical conditioning focuses on physiological responses to associated stimuli. To determine if co-robots can manipulate positive reinforcement (in the form of visual feedback) to influence the behaviors of the novices, this study was set up to focus on operant conditioning only and did not look at classical conditioning. Since this visual interface will be used in industries where humans will eventually need to operate equipment without the use of a co-robot trainer, learned behavior is imperative when determining the best instructional interface between co-robot and novice student.

We used visual reinforcements from the co-robot to help guide the participant through a learning task and then later tested participants without the guidance to determine which interface worked best as a teaching method. One interface used a more detailed guidance system and the other used a simple color change as reinforcement. The complex guidance interface was derived from a policy instruction algorithm where the simple visual feedback system was based on a simple positive reinforcement learning. Both test groups were later evaluated based on how well they learned the task by asking them to operate the equipment without guidance. Our hypothesis was that the more detailed interface would result in more learned skills. The result, however, was that the simple color changing interface was equally as effective as the complex guidance system.

CHAPTER II

LITERATURE REVIEW

The Construction Industry

Since construction is a very dangerous industry in which mistakes can cost both money and lives (Pinto, Nunes, & Ribeiro, 2011; Pinto, 2014; Simanaviciene, Liaudanskiene, & Ustinovichius, 2014; Sousa, Almeida, & Dias, 2014), construction training programs must consider the predictability and consistency in machine operator. Having a thorough knowledge and understanding of an individual's past behavior may help predict future behavior under the same conditions (Forward, 2009; Carrera, Muñoz, Caballero, Fernández, & Albarracín, 2012) which, in the construction industry, can prove useful when developing a more efficient training program.

Trainees in the construction industry come from a variety of backgrounds but are primarily young males (Bureau of Labor Statistics, 2014; Bureau of Labor Statistics, 2015) and have likely had exposure to visual reinforcement interfaces from their phone, computer, television, or tablet. In addition to visual feedback from phone and computer apps, trainees may also have experience with video games which use some of the same visual reinforcement strategies. With computers and smartphones being very common in western society, visual stimulation can be considered within the normal and accepted parameters of common positive reinforcement with regards to incoming trainees. Considering that experience plays a large role in how individuals learn a new task (Williams & Lombrozo, 2013), past exposure to similar visual reinforcements can influence strategies in the development of how co-robots can train new operators. With the creation of co-robotic training software and the requirement for operators to continually switch between looking at equipment and reading computer monitors, incorporating familiar visual positive reinforcement would potentially provide the most useful reinforcement tool for training.

Ditch Witch, for example, is developing computer simulators for use in their training programs. Initially focused on helping oil companies fix drilling equipment in the early 1900s, Ditch Witch eventually developed into a company focused on creating machinery that would adapt with the times and serve the needs of construction and installation in more urban and developed environments (Ditch Witch, 2016). Current training tools used at Ditch Witch utilize a step by step process of computer simulators, interaction with equipment in a safe environment, and finally hands-on operation of heavy equipment in a practice yard. The company also developed a computer simulator that incorporates visual feedback as part of the training tool and mimics what operators would see in reality. Part of this simulation involves the use of two joysticks with prompted cues as to when to move these sticks or press additional buttons. The simulator is designed to help habituate the user to dual-handed controls while teaching them to read and adjust input based on both mechanical (real world) and gauge (screen) feedback. Such training simulators have been shown to indicate future performance on actual instrumental vehicles (Santos, Merat, Mouta, Brookhuis, & de Waard, 2005) and can be a valid first step in the training process.

The use of computers in training for real-world experiences has potential for even further development. For example, studies of younger populations suggest that there is transfer of knowledge and skill from computer screens to physical tasks (Moser et al., 2015). Furthermore, simple interfaces may be preferred since evidence suggests that complex skills are best learned through static diagrams rather than complex animation (Khacharem, Zoudji, & Kalyuga, 2015). However, there is additional evidence to suggest that learning one physical task while simultaneously completing another may actually improve the training for the learned task (Feghhi & Valizade, 2011). This further supports the model that training with multiple interactions may be beneficial for construction trainees who will be incorporating multiple tasks into each job. This study incorporated both basic reinforcement learning as well as more complex interfaces in order to determine which learning environment was best for teaching and training novices.

Different interfaces expose the user to different degrees of stimuli and different leaning strategies. Generalized learning that is dependent on cue-based feedback and operant conditioning is better for adaptive behavior in later situations and has been shown to be more effective than direct learning (Pachur & Olsson, 2012) especially if it is presented in a linear format (Soyer & Hogarth, 2015). When considered in the context of a self-regulated learning environment, this corresponds to studies indicating that multiple levels of media in the learning environment helped improve both factual and integrated conceptual understanding which were directly related to the learning outcomes (Greene, Hutchison, Costa, & Crompton, 2012) and supported the knowledge building process of optimal learning (Kim, 2015). By incorporating more dependence on screens and computers as part of the learning and operation of these machinery, construction companies allow for greater opportunities in the development of software that can be later incorporated into existing training scenarios without changing a large amount of the training tools or processes.

The continually changing environment of construction and heavy machinery also dictates the need for operators to be able to problem solve under different conditions. For example, machine operators need to adjust techniques depending on different soil, weather, temperature, and traffic conditions. In this case, a training paradigm must take into account the necessity to train problem solving skills. Much like operation of machinery and computers, the ability to expand and develop analytical problem solving skills is dependent upon relevant experience and background knowledge (Anderson & Fincham, 2014).

Learning Theory

In learning theory, operant conditioning is accomplished through reinforcement and punishment with optimal learning occurring through positive reinforcement feedback, which, when combined with guided training (Clouse, 1997), can improve self-efficacy and confidence which consequently improves performance (Bandura, 1978; Bensadon, 2015). Such training scenarios and feedback must be adapted to the individual and therefore may change depending on the context and background of the individual learning (Mooi & Mohsin, 2014; Katahira, 2015). When appropriately used in training, positive reinforcement can help shape behaviors which, under the reinforcement training, can be used to predict future behaviors (Yechiam & Ert, 2007) especially if the individual has vivid memories of successes within that same environmental context (Nikolova, Lamberton, & Haws, 2015). With relation to the development of co-robots in construction, an understanding of novices' past experiences with positive visual reinforcements through smartphone or computer interfaces can assist with the development of guidance interfaces that utilize these same reinforcements.

Past and present environmental feedback are important in shaping behaviors, but self-reflection and confidence also influence learning. For example, self-perceived potential and motivation has been shown to be a good indicator of performance in young populations (Schniter, Sheremeta, & Shields, 2015; Wang, Morin, Liu, & Chian, 2015) and increases behavioral intentions with skill-intensive tasks (Passyn & Sujan, 2012). The actual acquisition of new motor skills, however, is dependent upon the involvement of existing skill sets (Latash, 2008). These studies, although primarily based in classic behaviorism, are part of a growing trend towards studies that incorporate both behavioral and cognitive psychology and focus on the idea that, while neural pathways are responsible for behaviors, they can be trained based on environmental feedback which can result in changes in individual behavior (Greenough, Larson, & Withers, 1985; Izquierdo et al., 1992; Tryon, 1993; Lacasse, 2015).

Complex Stimuli in Learning Environment

Visual guidance and teaching through computer screens poses challenges with regards to managing stimulation overload, graphical interfaces, and multitasking. With regards to environmental stimulation, researchers have found that employees demonstrated poor performance when working in high stimulus surroundings (Oldham, Kulik, & Stepina, 1991) or when they were subjected to information overload (Jackson & Farzeneh, 2012). Studies in visual learning suggest that individuals retained more information when learning through a simple graphic display rather than a more complex animated version or even static pictures (Fong, Lilly, & Por, 2012) and subjects often remember tasks better when there are fewer objects even if complexity varied (Luria & Vogel, 2011). Reduced performance resulting from stimulus overload is further supported with studies indicating that increased computer stimulation also elevates stress in the user (Lee, Son, & Kim, 2016) and that participants make decisions more easily when information and variation between choices is limited (Pilli & Mazzon, 2016). There are individual variations, however, since some people can process multiple stimuli and organize tasks to accomplish a goal (Reissland & Manzey, 2016) and participants with higher comprehension and prior understanding of a task perform better under learning environments similar to their past experiences (Tsai, Huang, Hou, Hsu, & Chiou, 2016). In general, though, studies indicate that people prefer tasks with lower complexity (Wickens, Gutweiller, & Santamaria, 2015) which further supports the need for simple learning interfaces with co-robots. The review of existing literature suggests that a simple guidance interface may be more effective than complex systems in co-robot training.

Behavior and Emotion

Although heavy machinery is becoming increasing semi-autonomous at some level, physical operation of the equipment will still be at least partially in the control of the operator. Because of this, the behavioral patterns and the repercussions of these patterns with regards to mechanical operation needs to be taken into account. Individuals require active engagement in learning a skill (Barnett et al., 2016; Buszard, Farrow, Zhu, & Masters, 2016) which requires them to have full awareness and control over their physical function. Behavioral changes are often influenced by emotion changes and motivations (X. Wang, 2011; Butz, 2013; Harth, Leach, & Kessler, 2013; Sinclair, 2013; Baillon, Koellinger, & Treffers, 2015; Forrest, Smith, Fussner, Dodd, & Clerkin, 2015; Martinussen, Sømhovd, Møller, & Siebler, 2015; Stussi, Brosch, & Sander, 2015) and the operation of machinery (Hu, Xie, & Li, 2013; Jeon, Walker, & Yim, 2014). Furthermore, existing psychological conditions can influence the ability to learn or process rewards and reinforcements (Thoma, Norra, Juckel, Suchan, & Bellebaum, 2015) and perceived behavioral control (Roberts, O'Connor, & Bélanger, 2013; Meijer, Catacutan, Sileshi, & Nieuwenhuis, 2015; Oliver, Han, Bos, & Backs, 2015). Moreover, evidence suggests that individuals with a calm approach and emotional control have more control over their behavior under stressful conditions and are less likely to engage in risky behavior (Amstadter, 2008; Sinclair, 2013; Aldao & Tull, 2015; Baillon et al., 2015; Kahle, Miller, Lopez, & Hastings, 2015). Furthermore, the ability of an individual to handle stress is directly correlated with learning, self-regulated learning and problem solving (Ahmadi, 2015). This means that emotional conditions can directly influence learning and must therefore be considered in the context of training.

Emotional regulation promotes adaptive strategies that can influence performance (Wagstaff, Hanton, & Fletcher, 2013) and changes in emotional regulation can impact behavior (Christensen & Aldao, 2015). Current studies in emotional regulation in the context of physical activities focus primarily on sports context in which athletes need to regulate emotions in order to control behavior for the benefit and safety of the team (Gunnell, Crocker, Wilson, Mack, & Zumbo, 2013; Tamminen & Crocker, 2013). Furthermore the use of an Individual Zone of Optimal Functioning framework has shown to enhance skills and emotional regulation within the athletic community (Salminen, Liukkonen, Hanin, & Hyvönen, 1995; Woodcock, Cumming, Duda, & Sharp, 2012). On the other hand, there is some evidence to suggest there is limited effectiveness to emotional regulations in organizations (Dumbravă, 2014). With regards to construction, however, emotional regulation may prove to be a beneficial tool to improve behavioral consistencies and safety due to its use in physical activities.

Large machinery and construction often involve hazardous conditions and the operator of equipment needs to have full control over the physical operation of machinery in order to avoid harm or death of him/herself or others. Current training paradigms involve error and mistake-based models that allow users to learn from their mistakes which can result in better analytic potential when the user is asked to perform those same tasks under pressure (Zhu, Poolton, Wilson, Maxwell, & Masters, 2011). Similar types of trainings that involve generalized guidance rather than ones that use extreme detail have also shown that individuals learn the task better when given more opportunities to use learn skills (Mullen, Faull, Jones, & Kingston, 2015). These skills, once acquired and practiced, can become practiced motor skills (Frank, Land, & Schack, 2013) (and in some extreme cases, motor reactions) to avoid danger and harm to others (Kibele, 2006) which can potentially be of extreme value under hazardous conditions such as construction sites.

With this in mind, current training through physical interaction, simulators, and equipment use can help trainees to learn and make mistakes during the learning process which not only helps prevent future mistakes, but also creates the potential for improved motor performance under the inevitable pressure that comes with the risks of the industry. Therefore, when considering training scenarios in the construction industry, training paradigms need to consider the emotional regulation of the operator and their resulting behavioral and physical changes with regards to the machinery. This study looked into past experiences with similar equipment, but did not gather data with regards to emotional states and further research is needed to determine the effect of emotional changes on the interactions with co-robots in a training environment.

CHAPTER III

METHODOLOGY

The purpose of this study was to test the effectiveness of visual positive reinforcement strategies during the co-robot training scenario. The dependent variables were chosen to compare the effectiveness of a simple user guidance system compared to a more complex guidance system when training novices to use equipment. The simple interface (Fig. 1) relies on basic principles of operant conditioning in which the user is guided to repeat behaviors for which he or she has received positive reinforcement. In this study a green color signified a correct movement of the joystick and a red color signified a wrong movement. The more complex guidance system (Fig. 2) introduced arrows and directions in addition to color changes to assist the user in performing the task as close to the expert movements as possible. Since some simulators and video games use more complex systems to teach a task (Luria & Vogel, 2011), it was important to test whether a simple interface could achieve the same result.

A total of 113 participants (N = 113) volunteered for this study. The average age of participants was 23.7 with approximately 72% males and 27% females with 26.5% Asians, 33.6% Caucasian, and the remainder of varying self-reported ethnic descent. All volunteers were active students, faculty, or visitors in the psychology and engineering departments at Oklahoma State University in Stillwater, Oklahoma. All participants sat in a standard office chair and visualized a guidance system on a standard 15-inch computer screen set on a box slightly to their left as to not block the view of the remote-controlled excavator located directly in front of them on the floor.

Participants were randomly assigned to one of three groups upon their arrival with each group corresponding to a different user interface. Each participant was then asked to complete a short survey in which they were asked, via Likert scale, to describe their comfort level with the joystick, past experiences with similar two-handed joysticks, and how often they play video games (See Appendix A). Each participant was then given three trials to become familiar with the controls and equipment prior to the use of the interface and any recording of actions. The use of three practice trials was based on experience with volunteers who agreed to partake in practice attempts of the study prior to finalization. The researchers found that individuals felt adequately comfortable with controller use after three practice trials. This allowed for all users to gain general familiarity with the joysticks and actions associated with each movement. Once the participants finished the initial introduction, a research assistant would introduce them to the graphical user interface (GUI) on the computer screen and explain what the interface meant. Group 1 with the colored circles (see Fig. 1) would experience changes from red to green circles for each hand if the actions were congruent with expected or optimal actions. Group 2 had speed bars (Fig. 2) that integrated the color reinforcements of Group 1 with direction arrows giving more complex visual cues as to what the participants should do with regards to the joysticks. Group 3 was the control group who had blank screens.

Fig 1. Circle GUI

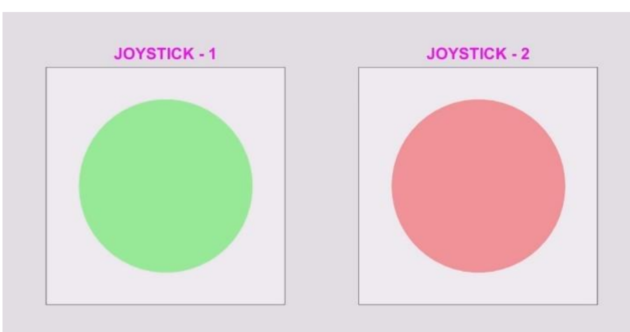
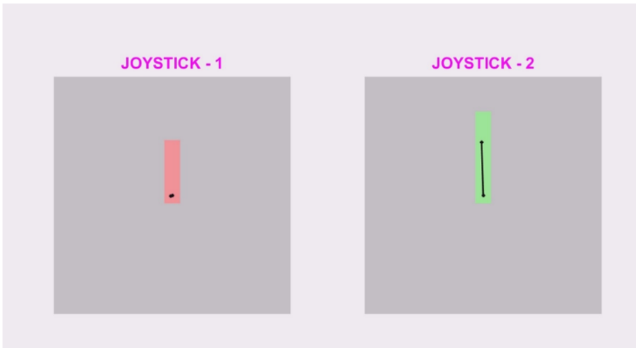
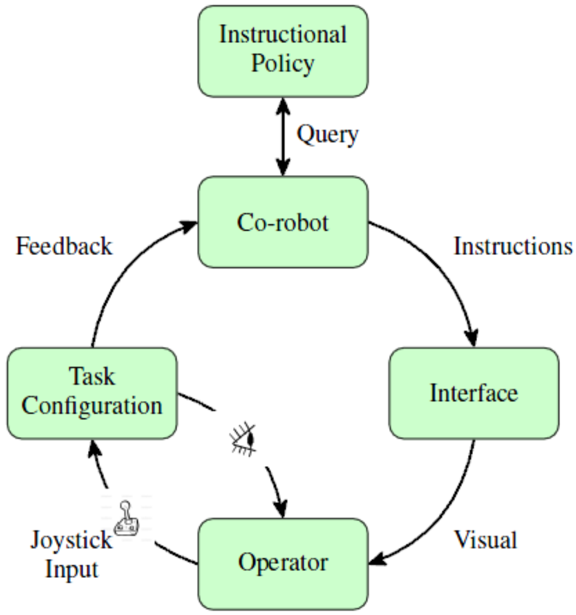


Fig 2. Speed Bar GUI



The visual interface appeared based on the flow diagram shown in Fig 3. Based on the interface designed by Harshal Maske, a member of the engineering team associated with the National Robotics Initiative, the co-robot utilized real time feedback through the joystick operation of the participant. In addition to information gathered through the computer based on joystick feedback, the co-robot also gathered information from the position of the excavator via ceiling-mounted cameras that tracked the movements of each marker on the excavator, truck, and sand bin (see Fig. 4). Optimal times and positions were determined based on movements captured by "experts" and the co-robot then adjusted the visual feedback to help guide the user to adjust his or her joystick movements to best match those of the expert. The instructional policy created for this part of the study was hand coded by Harshal Maske and was based on research in artificial intelligence, reinforcement learning, and learning from demonstration (Maske, Kieson, Chowdhary, & Abramson, 2016).

Fig 3. Instruction Interface Flow Diagram



The remote-controlled excavator was a fully hydraulic 1/14th scale model (Fig. 4) of 345D CAT Excavator. The model lacked joint-angle encoders and internal proprioception, hence all the experiments were performed inside a motion capture facility to ensure individual joint movements are captured in real-time and compared with optimal trajectories and actions. The motion capture facility included small physical markers on each joint of the excavator as well as interaction points for the cameras to locate the position of the sand bin and the truck. Ceiling-mounted cameras tracked the motion of the pins and relayed it back to the computer so that the computer could calculate positions, angle, and trajectory during each motion in relation to how the user manipulated the joystick.

Fig 4. Model Excavator and Truck

Participants were asked to complete a minimum of three initial trials (cycles) with the robotic excavator and then asked to return one to three days later (based on the availability of the participant) to perform additional cycles (also called Retests) without the help of the co-robot.

Once the participants started their interaction with the co-robot, times were recorded for each of these cycles and retests in addition to how many errors the participant made with regards to movements compared to those of experts. At the third retest cycle time, the researchers also counted how many times the participant hit the truck with the bucket of the excavator as well as how many movements (actions) were done by the truck to perform the task.

The goal was to determine if the GUI interfaces demonstrated improvement over the control group with regards to errors, actions, truck hits, changes in cycle times, and optimal end times and if each group demonstrated significant changes over the course of cycles with regards to errors or times. In addition, the researchers wanted to compare each group to the expert (for optimal actions and cycle time) but also to determine if there were significant differences between them.

Once the data was recorded, mean actions for each GUI group were compared to the expert number of actions (10.561) using a one sample t test and to each other through ANOVA to determine if there were significant differences. Mean truck hits were then averaged for each group and compared through ANOVA to determine if there were significant differences between them. Cycle errors were compared within each group through paired t tests and then retest 3 cycle errors were compared between groups with ANOVA to determine if there were significant differences. Times were compared within each group using paired t tests to determine significant changes over initial cycle times and retest times and compared between groups using ANOVA. They were also compared to the expert time (24.9s) through a one sample t test to determine if there were significant differences between resulting mean end times and expert (optimal) time.

Results from the survey regarding joystick comfort, use, and video game play were compared using Spearman's correlation to the end result times to determine if there were any significant correlations between past experiences and the resulting end time.

CHAPTER IV

FINDINGS

Participants and Measures

The purpose of this study was to determine the effect of different graphical user interfaces for training novice participants to perform a complex task. The study tested both a simple interface (colored circles) and a more complex interface (speed bars) in addition to a control (no interface) to determine how a co-robot interface would affect the learning of a skill in participants. Physical motion of the model excavator in addition to timed cycles (trials) were evaluated to determine the differences between the groups, similarities of each group to the optimal "expert" motions and times, and changes within each group with regards to errors and times. Participant actions were evaluated based on how many single motions it took for the participants to maneuver the excavator into the correct position (Mean Actions), the number of times each participant hit the truck with the bucket of the excavator (Truck Hits), and how many times they needed to correct their movements (Errors). Mean actions and truck hits were collected at the last retest time whereas the errors were counted at each cycle and all data were collected through video and analyzed with the help of research assistants. In addition to the physical motions of the excavator, each trial was timed and compared to other trials within the group as well as an optimal "expert" time set by the researchers.

A total of 113 participants (*N* = 113) were randomly sorted into groups: Group 1 using the Guidance User Interface (GUI) Circles, Group 2 using the GUI with Speed Bars, and Group 3 with no GUI (control). Each participant was instructed briefly on how the controllers work then given a minimum of three trials to attempt to scoop sand from the tub and deposit into the truck using the controls and the assistance of the selected training GUI.

Mean Actions

We define actions as the number of movements needed to complete the truck loading task. Averages for each group were compared against the expert average (*N* = 6, average number of actions = 10.561) in a one sample t test. Analysis of the distribution of the data showed outliers in each group (See Appendix B) so the data was then selected to only include mean actions greater than 2 and less than 26. The resulting data showed Group 1 (*N* = 32) with a mean of 14.71 (*SD* = 4.13), Group 2 (*N* = 39) with a mean of 14.28 (*SD* = 3.87) and Group 3 (*N* = 32) with a mean of 16.06 (*SD* = 3.87). Three data points were removed from Group 1, two from Group 2, and two from Group 3. The resulting ANOVA can be seen in Table 1, with the one-sample t tests in Table 2.

Table 1

Analysis of variance (ANOVA) of mean actions between all experimental groups

	Sum of Squares	***df***	**Mean Square**	***F***	***p***
Between Groups	58.39	2	29.20	1.84	.164
Within Groups	1587.67	100	15.88		
Total	1646.06	102			

Table 2

One-sample t test between mean actions of each group and expert (10.56)

					95% Confidence Interval of the Difference	
Experiment Group	***t***	***df***	**Sig**	**Mean Difference**	**Lower**	**Upper**
Group 1: GUI Circles	5.68	31	.00*	4.15	2.66	5.64
Group 2: GUI Speed Bars	5.88	38	.00*	3.72	2.44	5.01
Group 3: No GUI	8.04	31	.00*	5.50	4.10	6.89

**Significant at the p < .01 level.*

The results for the analysis of variance for actions was not significant $F(2,100) = 1.84$ (p = .164) and the one-sample t tests resulted in significant differences ($p < .01$) between the mean actions and the mean actions of the expert (10.56) for each group, suggesting no differences between the groups and no group demonstrating expert level accuracy with regards to actions.

Truck Hits

Truck hits were defined as the number of times the participant maneuvered the excavator in a way that caused a collision between the boom arm or shovel attachment and the model truck. The purpose of the trial was to scoop sand out of the plastic container and dump it into the truck without any faults or collisions. Experts would therefore have zero collisions and any collisions would be seen as an error of the novice during the trial. Ideal truck hits would therefore be zero. Stem and leaf plots for the distribution of data can be seen in Appendix C. A one-way ANOVA was conducted to determine significant differences between the groups (Table 4).

Table 3

Descriptive statistics for truck hits for all experimental groups

Experiment Group	***N***	**Minimum**	**Maximum**	***M***	***SD***
Group 1: GUI Circles	34	.00	12.00	.59	2.00
Group 2: GUI Speed Bars	41	.00	3.00	.29	.68
Group 3: No GUI	34	.00	4.00	.35	.95

Table 4

Analysis of variance (ANOVA) for truck hits between all experimental groups

	Sum of Squares	***df***	**Mean Square**	***F***	***p***
Between Groups	1.75	2	.87	.46	.63
Within Groups	202.49	106	1.91		
Total	204.22	108			

The ANOVA did not result in any significant results and therefore no significant differences were found between the groups with regards to truck hits.

Cycle Errors

Cycle errors were defined as the number of unnecessary motions made by the novice during the truck loading task. Cycle error averages were calculated for each group for cycle 1, cycle 3, retest 1 and retest 3 and descriptive statistics for each cycle and retest are displayed in Table 5. Paired t tests were conducted for comparing cycle 1 and cycle 3, cycle 3 and retest 1, and retest 1 and retest 3 (Table 6) and an ANOVA was used to determine significant differences between errors for each group at retest 3 (Table 7).

Table 5

Descriptive statistics for errors for each experimental group at cycle 1, cycle 3, retest 1, and retest 3

	Group 1: GUI Circles			**Group 2: GUI Speed Bars**			**Group 3: No GUI**		
	N	***M***	***SD***	***N***	***M***	***SD***	***N***	***M***	***SD***
Cycle 1	32	3.44	3.59	41	2.59	1.87	38	2.68	2.45
Cycle 3	32	2.63	2.44	41	2.71	2.74	38	2.34	1.89
Retest 1	20	2.4	2.06	27	2.30	1.73	35	1.86	2.10
Retest 3	21	1.38	1.12	27	1.26	1.32	35	1.29	1.25

Table 6

Paired sample t test for cycle errors within all experimental groups

					95% Confidence Interval of the Difference				
Experiment Group	**Paired Cycles**	***M***	***SD***	**Std Error Mean**	**Lower**	**Upper**	***t***	***df***	**Sig.**
Group 1: GUI Circles	Cycle 1 and Cycle 3	.81	3.15	.56	-.32	1.94	1.46	31	.15
	Cycle 3 and Retest 1	.90	3.16	.71	-.58	2.38	1.27	19	.22
	Retest 1 and Retest 3	1.00	2.00	.44	.09	1.91	2.29	20	.03**
Group 2: GUI Speed Bars	Cycle 1 and Cycle 3	-.12	2.55	.40	-.93	.68	-.31	40	.76
	Cycle 3 and Retest 1	-.22	1.99	.38	-1.01	.56	-.581	26	.57
	Retest 1 and Retest 3	1.04	1.99	.38	.25	1.82	2.71	26	.01**
Group 3: No GUI	Cycle 1 and Cycle 3	.34	2.52	.41	-.49	1.17	.84	37	.41
	Cycle 3 and Retest 1	.46	2.75	.46	-.49	1.40	.98	34	.33
	Retest 1 and Retest 3	.57	1.70	.29	-.013	1.16	1.98	34	.055

***Results significant at the p < .05 level*

The results of the paired samples t test revealed in significant differences between retest 1 and retest 3 for both Group 1 and Group 2. The paired t test between retest 1 and retest 3 for group 1 resulted in $t(20) = 2.29$ which was significant ($p = .03$, $p < .05$) and the paired t test for between retest 1 an retest 3 for group 2 resulted in $t(26) = 2.71$ which was significant ($p = .01$, $p < .05$). The findings for the paired sample t tests for errors suggests that groups experiencing the colored circle and speed bar GUIs demonstrated significant change in error where the group without a GUI showed no significant change in error over the course of the study.

The errors for retest 3 were then compared between the groups using ANOVA. The results can be seen in Table 7. Despite Group 1 and Group 2 showing significant differences within their own groups, the results of the ANOVA suggest there was no significant differences (p = .94) between all experimental groups with regards to errors at retest 3.

Table 7

Analysis of variance (ANOVA) for errors at retest time 3 between all experimental groups

	Sum of Squares	***df***	**Mean Square**	***F***	***p***
Between Groups	.19	2	.10	.06	.94
Within Groups	123.28	80	1.54		
Total	123.47	82			

Cycle Times

Each participant was asked to complete the task at least three times and each cycle was timed. Means were calculated for each cycle/trial for each group for both original and retest cycle times. Paired t tests were then conducted to compare the times of cycle 1 to cycle 3, cycle 3 to retest 1, and retest 1 to retest 3. An ANOVA was used to compare the timed results of retest 3 and a one-sample t test was used to compare retest 3 times with the expert time (24.9s).

Analysis of the distribution of data showed extreme outliers for Group 1 and Group 3 (See Appendix D), consequently data were selected to only include retest times that were less than 65s.

Two cases were removed from Group 1 and one case was removed from Group 3. The results of the paired samples t tests can be seen in Table 8.

Table 8

Paired sample t test for cycle times within all experimental groups

					95% Confidence Interval of the Difference				
Experiment Group	**Paired Cycles**	***M***	***SD***	**Std Error Mean**	**Lower**	**Upper**	***t***	***df***	***p***
Group 1: GUI Circles	Cycle 1 and Cycle 3	2.78	18.06	3.41	-4.22	9.79	.82	27	.42
	Cycle 3 and Retest 1	3.39	26.30	4.97	-6.8	13.59	.68	27	.50
	Retest 1 and Retest 3	18.62	22.16	4.12	10.19	27.05	4.53	28	.00*
Group 2: GUI Speed Bars	Cycle 1 and Cycle 3	9.04	43.39	8.51	-8.49	26.56	1.06	25	.30
	Cycle 3 and Retest 1	3.19	27.39	5.37	-7.87	14.25	.59	25	.56
	Retest 1 and Retest 3	6.12	17.74	3.48	-1.05	13.28	1.76	25	.09
Group 3: No GUI	Cycle 1 and Cycle 3	7.41	34.14	6.57	-6.10	20.91	1.13	26	.27
	Cycle 3 and Retest 1	8.26	38.14	7.34	-6.83	23.35	1.13	26	.27
	Retest 1 and Retest 3	10.76	22.29	4.14	2.28	19.24	2.60	28	.02**

**Results significant at the $p < .01$ level*
***Results significant at the $p < .05$ level*

The results of the paired samples t test for cycle times suggests there were no significant differences between times for cycle 1 and cycle 3 or between cycle 3 and retest 1. Group 1 (M = 18.62, SD = 22.16) and Group 3 (M = 10.76, SD = 22.29) showed significant differences between retest 1 and retest 3 ($p < .05$; $p = .02$, $p < .05$ respectively). This suggests that both Group 1 with the circle GUI and the control group demonstrated significant changes in time during the retest.

Table 9

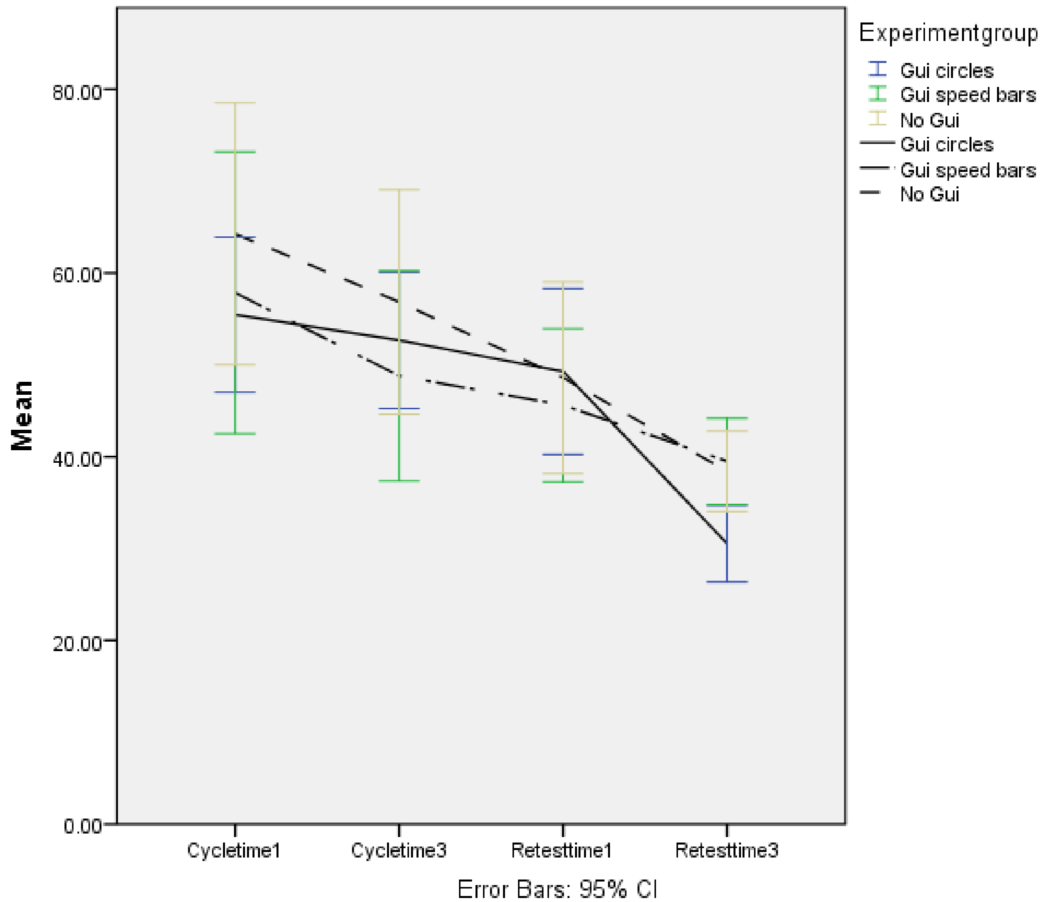
Analysis of variance (ANOVA) for times at retest time 3 between all experimental groups

	Sum of Squares	***df***	**Mean Square**	***F***	***p***
Between Groups	1592.99	2	796.50	6.41	.00*
Within Groups	10068.569	81	124.30		
Total	11661.56	83			

**Significant at the p < .01 level.*

The ANOVA for retest 3 times (Table 9) showed that the difference in retest 3 times between groups was significant $F(2,81) = 6.41$ ($p < .01$) suggesting significant differences between at least two of the groups. Tukey post-hoc comparisons were performed and resulted in significant differences between retest 3 times for Group 1 and Group 2 ($p < .01$) and between Group 1 and Group 3 ($p < .05$), suggesting that those who used the circle GUI demonstrated significant differences in their retest 3 times when compared to the other two groups. Figure 5 shows the mean times for each group with corresponding error bars at cycle time 1, cycle 3, retest 1 and retest 3.

Fig. 5 Mean Cycle Times and Corresponding Errors for Experimental Groups



To determine how close each group came to the expert time of 24.9s, a one-sample t test was performed with each groups' retest 3 times. For retest 3 the mean for Group 1 (*N* = 29) was 30.21 (*SD* = 10.73), the mean for group 2 (*N* = 26) was 39.50 (*SD* = 11.611) and the mean for group 3 (*N* = 29) was 39.24 (*SD* = 11.13). The result of the one sample t test can be seen in Table 10.

Table 10

One-sample t test between retest 3 times of each group and expert (24.9)

					95% Confidence Interval of the Difference	
Experiment Group	***t***	***df***	***p***	**Mean Difference**	**Lower**	**Upper**
Group 1: GUI Circles	2.66	28	.013**	5.31	1.22	9.39
Group 2: GUI Speed Bars	6.41	25	.00*	14.60	9.91	19.29
Group 3: No GUI	6.94	28	.00*	14.34	10.11	18.58

**Significant at the p < .01 level.*
***Significant at the p < .05 level*

The results of the one-sample t test suggest that all of the groups' times for retest 3 were significantly different from the expert.

Past Experience and Test Results

The questions on the survey regarding comfort with the controller, past controller use, and game play (See Appendix A) were based on a Likert-type scale and the data were collected and compared to the final retest 3 times to determine any correlation. Outliers were left out and all groups were combined (*N* = 83). A Spearman's correlation was performed and the results are in Table 11

Table 11.

Correlations between retest 3 times and controller comfort, controller use, and game play

	Controller Comfort	**Controller Use**	**Game Play**
Retest 3	.09	.15	.05

No significant correlations were discovered between retest time 3 and the Likert responses of participants for controller comfort, controller use, or frequency of game play.

Summary

The overall findings of this study found no significance difference between groups with regards to mean actions and no closeness between the actions of each group and the expert (10.51). Similarly, there were no significant differences between groups with regards to truck hits. Significant changes in errors were found, however between retest 1 and retest 3 in Group 1 (M = 1.00, SD = 2.00) $t(20) = 2.29$ ($p = .03$, $p < .05$) and Group 2 (M = 1.04, SD = 1.99) $t(26) = 2.71$ ($p = .01$, $p < .05$) suggesting participants using visual guidance demonstrated greater changes in movement errors than those without a GUI.

Paired sample tests for times resulted in significant changes between retest 1 and retest 3 times for both Group 1 (M = 18.62,SD = 22.16) $t(28) = 4.53$ ($p < .05$) and Group 3(M = 10.76, SD = 22.29) $t(28) = 2.60$ ($p < .05$, $p = .02$) and an ANOVA test resulted in only Group 1 having retest 3 times that were significantly different $F(2,81) = 6.41$ ($p <.05$) than the others at retest 3. These tests suggest that Group 1 and Group 3 had more significant changes towards the end of the cycles than did Group 2, however, the resulting retest 3 times only showed a significant difference ($p < .05$, $p = .02$) between Group 1 and the other two groups. This suggests that not only did Group 1 demonstrate significant change towards the end, but the resulting time was significantly different than the other groups. When compared to the expert time (24.9s), however, no groups demonstrated values that corresponded with the expert, suggesting that all groups remained significantly different at retest time 3 when compared to the optimal time.

Correlation tests between the survey and retest 3 found no significant results.

The findings indicate that only changes in errors and times showed any significance when comparing different interfaces. Based on the results, visual interfaces seem to provide some improvement over the control with regards to errors and, although there were significant changes in cycle times for Group 1 (GUI Circles) and Group 3 (No GUI) over the duration of the cycles, all groups remained significantly different than the expert at the end of the retests. Group 1, however, showed significantly different times at the end than the other two and came closest to the expert time of 24.9s.

CHAPTER V

CONCLUSION

The goal of this study was to test two user interfaces (one simple and one more complex) to determine which visual interface would provide the most effective teaching tool from which the novice could learn. The result was somewhat surprising in that the simpler interface slightly outperformed the more complex one, demonstrating that a very simple visual reinforcement strategy may obtain greater results when robots are used to teach humans a skill set. This supports some studies that suggest that less-complex learning systems may be suitable for learning for both human and robots (Tangkaratt, Morimoto, & Sugiyama, 2016) and that less guidance in learning may allow for greater learning potential in humans (Paas, Tuovinen, Tabbers, &Van Gerven, 2010; Van Merrienboer, Kester, & Paas, 2006). Since both visual displays showed improved learning over the control group, we can conclude that simple visual feedback can help assist in human learning from co-robots and more complex interfaces may not be necessary. This is especially evident in Fig. 5 which shows the changes in means for each test time and the differences between the end times. The conclusions may be biased, however, since the participant pool was largely well-educated college-level participants who are not necessarily representative of the target population of construction workers.

Although there was no significant difference between the two groups during the retest, a number participants in Group 2 (Speed Bars) who verbalized that the interface was a bit distracting which further supports the idea that a simple visual reinforcement tool is equally as effective at teachingthe task. The result would be less distracting co-robot interfaces that result in retained information in the human learner. When considering the use of such co-robots in the construction industry, for example, less visual input would reduce stimulant load for the operator and would result in improved safety and situational awareness.

Co-robots, Cobots, and autonomous robotic partners are being designed by multiple industries to provide not only teaching tools, but also trusted working partners. In some cases infrared sensors are being tested to improve robot responses to human interaction and create more dynamic learning environments for the robot and human (Salter & Dautenhahn, 2006) and some scientists are developing robots that can better read human emotional responses in a learning environment (Singh, Karanam & Kumar, 2013). The interaction between human and robot in a learning environment has a lot of potential for growth especially through competition-based systems (Morita, Jitsev, & Morrison, 2016). The combination of research in this area will likely lead to the integration of improved visual interfaces and better learning environments for humans from the co-robot instructors.

The idea that humans may retain more information by learning with simple interfaces may eventually play a larger role in how we interact with the evolving digital world. Smartphones, tablets, and laptops are only a few of the ways our technology travels with us. This, of course, gives people the ability to access information at almost any given time. It also means that we increasingly rely on that access to help guide us through daily interactions like navigation, finding relevant news, and even personal interactions. This increasing reliance, however, may eventually mean that we lose the ability to function without our technology under these specific circumstances. Our electronics, like robotic guidance systems, walk us through the process of obtaining information or reaching our goals without actually teaching us in a way that allows us to get there on our own. Not only does this create a dependence on our technology, but also perhaps means that we may not be capable of performing those same tasks without the help of our technological guidance systems.

The growing number of interactive devices in our environment may, in fact, increase our stress and reduce our ability to retain information and learn tasks. Too much stimulation or information can reduce productivity (Jackson & Farzaneh, 2012; Oldham et. al., 2017) and simple descriptions are often more easily remembered than complex ones (Luria & Vogel, 2011). Furthermore, if participants are asked to engage in multiple tasks at once, stress increases and performance declines (Paas et. al., 2010; Reissand & Manzey, 2016). This further supports the idea that individuals in a complex learning environment may perform and learn better when stimulus and stress are reduced. Part of this may involve adapting co-robot interfaces that are simpler and provide basic feedback rather than complex guidance.

This study helps explore the ways technology can guide or, in some ways, impede our ability to learn from our environment. Perhaps this could open discussions for more ethics in terms of how much technology needs to be a part of our lives versus a means of dependence for humans on electronics. It may also mean the development of applications or interactive software that creates opportunities for individuals to learn rather than depend. Understanding how we, as humans, interact and learn from our technological (and eventually robotic) environment may give us more insight into what it means to be human in a growing world of electronic intelligence.

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APPENDICES

Appendix A. Pre-trial Survey

Survey 1. Pre-Trial Questionnaire

Participation Survey (Given BEFORE experiment)

General Information:

Gender: F M O (other)

Age: _________

Ethnicity:___________

Background Questions:

How would you classify your mood today? ______________

How would you classify your energy level? (circle one) Low Medium High

How comfortable do you feel using remote-controlled equipment?

	1	2	3	4	5
Not comfortable					Very comfortable

How comfortable do you feel using two-handed controls such as video game controllers or the hand-held controllers used in this study?

	1	2	3	4	5
Not comfortable					Very comfortable

Appendix A. (Cont.'d)

How often do you use two-handed controllers such as video game controllers or the hand-held controllers used in this study? (in this case 1= not at all, 2= occasionally, 3= a few times a month, 4 = at least once a week, 5 = every day)

	1	2	3	4	5
Not at all					Every day

How often do you play video games?

	1	2	3	4	5
Not at all					Every day

Have you every driven construction equipment, heavy machinery, or tractors? Y N

If Yes, how often have you/do you use or drive heavy equipment or machinery?
(in this case 1= not at all, 2= occasionally, 3= a few times a month, 4 = at least once a week, 5 = every day)

	1	2	3	4	5
Not at all					Every day

Appendix B. Data Distribution for Mean Actions

Mean actions Stem-and-Leaf Plot for
Experiment group = **Gui circles**

Frequency	Stem & Leaf
1.00	Extremes (=<3)
1.00	0 . 6
14.00	1 . 01112222233344
12.00	1 . 555666677889
4.00	2 . 0113
2.00	Extremes (>=27)

Stem width: 10.00
Each leaf: 1 case(s)

Mean actions Stem-and-Leaf Plot for
Experiment group = **Gui speed bars**

Frequency	Stem & Leaf
1.0	Extremes (=<2)
.00	0 .
3.00	0 . 588
21.00	1 . 000011111222333344444
12.00	1 . 555667899999
3.00	2 . 012
1.00	Extremes (>=28)

Stem width: 10.00
Each leaf: 1 case(s)

Mean actions Stem-and-Leaf Plot for
Experiment group = **No Gui**

Frequency	Stem & Leaf
1.00	0 . 7
12.00	1 . 000333334444
15.00	1 . 555566677888999
4.00	2 . 1234
2.00	Extremes (>=29)

Stem width: 10.00
Each leaf: 1 case(s)

Appendix C. Data distribution for Truck Hits

Truck hits Stem-and-Leaf Plot for
Experiment group = **Gui circles**

```
Frequency    Stem &  Leaf

  29.00        0 .  00000000000000000000000000000
   5.00        Extremes    (>=1)

Stem width:     10.00
Each leaf:       1 case(s)
```

Truck hits Stem-and-Leaf Plot for
Experiment group = **Gui speed bars**

```
Frequency    Stem &  Leaf

  33.00        0 .  000000000000000000000000000000000
   8.00        Extremes    (>=1)

Stem width:     10.00
Each leaf:       1 case(s)
```

Truck hits Stem-and-Leaf Plot for
Experiment group = **No Gui**

```
Frequency    Stem &  Leaf

  29.00        0 .  00000000000000000000000000000
   5.00        Extremes    (>=1)

Stem width:     10.00
Each leaf:       1 case(s)
```

Appendix D. Distribution of Data for Retest 3 times.

Retesttime3 Stem-and-Leaf Plot for
Experiment group = **Gui circles**

Frequency	Stem & Leaf
3.00	1 . 999
13.00	2 . 0000112335589
8.00	3 . 24456679
4.00	4 . 1467
.00	5 .
1.00	6 . 1
2.00	Extremes (>=65)

Stem width: 10.00
Each leaf: 1 case(s)

Retesttime3 Stem-and-Leaf Plot for
Experiment group = **Gui speed bars**

Frequency	Stem & Leaf
2.00	2 . 34
4.00	2 . 6679
5.00	3 . 11233
3.00	3 . 668
2.00	4 . 00
6.00	4 . 678999
.00	5 .
2.00	5 . 57
2.00	6 . 02

Stem width: 10.00
Each leaf: 1 case(s)

Appendix D. (Cont'd)

Retesttime3 Stem-and-Leaf Plot for
Experiment group = **No Gui**

Frequency	Stem & Leaf
2.00	2 . 01
2.00	2 . 58
8.00	3 . 00011234
5.00	3 . 56889
1.00	4 . 1
5.00	4 . 66689
3.00	5 . 223
2.00	5 . 67
1.00	6 . 1
.00	6 .
1.00	7 . 2
1.00	7 . 6
1.00	Extremes (>=85)

Stem width: 10.00
Each leaf: 1 case(s)

VITA

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