TRANSFER OF TRAINING FROM VIRTUAL REALITY ENVIRONMENTS

A Dissertation by

Christopher James Hamblin

Master of Arts, Wichita State University, 2003

Bachelor of Science, Central Missouri State University, 1997

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I have examined the final copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy with a major in Psychology/Human Factors.

Alex Chaparro, Committee Chairperson

We have read this dissertation and recommend its acceptance

Barbara S. Chaparro, Committee Member

Charles G. Halcomb, Committee Member

Michael Jorgensen, Committee Member

Daniel McConnell, Committee Member

Accepted for the College of Liberal Arts and Sciences

William Bishoff, Dean

Accepted for the Graduate School

Susan Kovar, Dean

DEDICATION

To my hero, Raymond D. Rider, for showing me the power of courage and persistence.

To my Mother who shaped the person I am today.

Most especially to my incredible wife Kyndra and my daughters Bryanna and Baylee whose unconditional love, unwavering support, and selfless sacrifice have made this work possible.

All men dream: but not equally.

Those who dream by night in the dusty recesses of their minds

wake in the day to find it was vanity:

but dreamers of the day are dangerous men,

for they may act on their dreams with open eyes,

to make them possible.

T.E. Lawrence,
Seven Pillars of Wisdom

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ABSTRACT

This study evaluated the transfer of training and training efficiency of two virtual reality environments (head-mounted display and personal computer) for a complex manual assembly task. Transfer of training was measured by comparing the post-training performance of two virtual training groups, a real-world training group and a control group that received no training. All training groups were taught to assemble a Lego™ forklift model in their respective environment. After training, participants assembled a real-world model of the forklift as well as a novel model of a racecar, which required the same parts as the forklift assembled in a different configuration. Results from this study show that virtual environments can be effective training simulators for complex assembly tasks although they are less efficient than real-world training. The results also suggest that individual differences such as general intelligence, spatial aptitude, and computer user self-efficacy influence one's ability to learn in a virtual environment.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

One of the most promising means of human-computer interaction (HCI) is virtual reality (VR). VR makes use of a variety of technologies that allow users to interactive with computer-generated environments with a first-person perspective. These technologies create a sense of "presence" within the environment by immersing the user into a multi-sensory experience that can include visual, auditory, haptic, and tactile feedback to the user. Virtual interfaces allow users to move about and interact with virtual objects or virtual characters in ways that are potentially more engaging than methods afforded by the traditional desktop environment.

VR emerged in the mid-1980s as the development of high-performance computers increased in storage capacity and processing speed. In the mid-1990s the development of low-cost personal computers (PC) together with inexpensive high-resolution graphics cards led many technologists and researchers to believe that VR technologies would be ubiquitous by the end of the 20th Century. Many boldly predicted that VR technologies would be the next generation PC with one in every home, office and classroom (Durlach and Mavor, 1995).

Unfortunately, the lofty promises made by technologists have not yet been realized. The relatively high cost of VR technologies coupled with a general misunderstanding of its abilities and limitations have relegated its applications to military and academic research as well as entertainment (i.e., movies and video games).

Due in part to Hollywood and the popular media's exaggerated depiction of VR, there is a misunderstanding of its capabilities and applications. Often, when the term virtual reality is used, people think of movies such as "The Matrix" or "Lawnmower Man" in which a person outfitted with a head-mounted display is immersed into perceptually stunning or realistic-looking environments. This notion of virtual reality often creates an unrealistic expectation of VR and its capabilities.

The terms virtual reality and virtual environment can also be a source of misunderstanding as they are often used interchangeably; however, it is important, especially in the context of this study, to make a distinction between the two. In this study the term virtual reality is used to describe, in general terms, the technologies used to create and interact with the virtual environment (i.e., computers, graphics cards, input devices, display devices, software, etc.), while virtual environment is used specifically to describe the artificial three-dimensional space and geometry with which the user interacts. There are several definitions of the term virtual environment; however, this study will define a virtual environment as any digital three-dimensional space that depicts an environment populated with objects that can be manipulated. This definition includes three-dimensional environments displayed on desktop computer screens such as those depicted in first-person video games or three-dimensional computer-aided drafting programs, projected virtual environments (i.e., CAVEs and PowerWalls) and full-immersive virtual worlds.

While VR has failed to become a widely applied technology, continuous advancements in computer technologies coupled with the decreasing costs of computer processors continue to offer promise for the broader application of VR technologies. One application that seems to hold particular promise is simulation-based training. VR allows computer programmers the ability to simulate real-world environments. In 1995, the American National Research Council published a report regarding the state of VR research and made recommendations for its future development (Durlach and Mavor 1995). The report suggested that VEs have the potential to broaden the application of simulator-based training and provide advantages that are not present in real-world simulators. For example, VEs can enhance training by augmenting the training scenario with information not available in a real-world training environment. Darken and Sibert (1996b) used VR to manipulate environmental variables (i.e., furniture, paintings, etc.) to identify cues used for wayfinding strategies in large office buildings. Their study highlighted one of the key advantages that VEs provide in the ability to alter an environment quickly and easily. Other researchers have demonstrated that VR's ability to augment training environments can have positive affects on learning. Piller and Sebrechts (2003) have found that trainees develop more accurate and thorough spatial models when the walls of buildings are made transparent. Durlach and Mavor (1995) also suggest that VR training is advantageous because of the ability to simulate real-world environments that are too dangerous or expensive to replicate in the real world (i.e., training firefighters to navigate burning buildings or medical doctors to perform telerobotic surgical procedures).

Unfortunately, subsequent studies investigating the effectiveness of training from VEs show mixed results, which paint a confusing picture for the application and use of VR as a training tool. There are several explanations for these results, but a review of the literature suggests that the some of peripheral devices used in studies may not be appropriate for training certain tasks.

The term "Virtual Reality" is used throughout the literature to describe a wide array of display devices, input devices, and software applications. VR display devices include typical desktop monitors and stereoscopic head-mounted displays (HMDs) as well as projective immersive displays such as CAVEs or PowerWalls. Input devices can include a typical PC mouse, three-dimensional joysticks, or direct object manipulation devices (i.e., cybergloves and pinchgloves) to name a few. These devices are mixed and matched throughout the literature as researchers employ the devices that are available to them. Often researchers use devices merely because they are compatible with the computer platform or other peripheral devices they are using. However, each of these devices offers unique affordances and constraints that may aid or hinder the acquisition of skill or knowledge depending upon the specific training application.

Another potential explanation for the mixed results may be attributed to individual differences of the subjects participating in the studies. HCI studies have found that individual differences such as gender, age, prior experience, and user confidence influence one's ability to interact with computers (Badagliacco, 1990; Bandura, 1997; Chen, 1986; Eachus and Cassidy, 2002). These same variables have been shown to affect learning and transfer; yet, with few exceptions, these variables are rarely measured in studies evaluating transfer of training from VEs. As with any training device, the effectiveness of virtual simulators will depend on their ability to match or augment the cognitive characteristics of the trainee (Card, Moran and Newell, 1983)

The goal of this research is to determine what type of VE best accommodates transfer of training for a complex manual assembly task. This research will also attempt to determine if individual differences known to mediate user performance in HCI play a role in the transfer of training that occurs from VEs.

Transfer of Learning

The effectiveness of any training device is determined by the ability of the trainee to transfer the knowledge learned during training to a new task. The ability to apply what is previously learned from one task to another is referred to as *transfer*. For virtual training, transfer effectiveness is determined by the amount of transfer that occurs from one environment to another.

The study of transfer is controversial and has been argued since it first received attention in the beginning of the 20th Century (see Judd, 1908 and Thorndike and Woodworth, 1901). At the center of the debate is the issue of general versus specific transfer and the question as to which theory is most appropriate for learning. Theories of general transfer are based upon beliefs that abstract knowledge can be applied more broadly to a wide array of tasks and contexts. For example, it was long believed that the study of Latin improved understanding and application of language and therefore should be the focus of education. On the other hand, theories of specific transfer propose that transfer occurs only when two tasks share similar elements or a person has sufficient expertise in a specific domain of knowledge.

More contemporary theories of transfer suggests that the phenomenon is indistinguishable from other learning theories and therefore requires no special consideration (Gick and Holyoak, 1987, p. 10),

> No empirical or theoretical chasm separates transfer from the general topic of learning. Rather, the consequences of prior learning can be measured for a continuum of subsequent tasks that range from those that are merely repetitions (self-transfer), to those that are highly similar (near-transfer), to those that are very different (far transfer).

Gick and Holyoak (1987) state that transfer is solely dependent upon a person's ability to perceive the common relationship between two tasks. This proposition potentially unifies both general and specific theories of transfer allowing for either to occur provided that the trainee is aware of the similarities between the tasks.

Gick and Holyoak (1987) suggest that elements of a task should be distinguished by their relationship to the outcome or goal attainment. If elements are causally or functionally related to the outcome they are referred to as *structural,* while those not related to the outcome are referred to as *surface.* This discrimination is important in determining if the direction of transfer is positive or negative. If two tasks share surface and structural similarities then transfer will be positive; however, if two tasks share surface similarities but are structurally dissimilar the possibility of negative transfer increases. This has implications for virtual training environments used to train manual assembly tasks where the visual stimuli, which should be considered as a surface feature, replicate the real world but interface with the environment (causal features) are mediated by the by an input device that may or may not be compatible to the physical movements required for the assembly.

If the quantity and direction of transfer is determined by perceived similarity then the context of the learning environment plays a key role in determining transfer (Gick and Holyoak, 1987). When environments or situations are similar, relevant information is accessed and transfer occurs; the greater the similarity the greater transfer. However, if the context of the transfer task is significantly different from the training task, then prior knowledge may not be retrieved. This is an important consideration for virtual simulators since current technologies limit the types of interaction that can be performed in VEs. For a complex task involving both cognitive and motor skills, this issue becomes especially important since researchers must consider not only the perceptual aspects of the environment but the psychomotor aspects as well.

The physical movements that people make when performing a task provide kinesthetic and vestibular feedback, which may be important cues when learning and recalling a psychomotor task. Schmidt and Young (1987) state: "every motor response (except perhaps simple reflexes) has a perceptual-cognitive component and requires at least minimal decision making" (p. 47). This suggests that performing a specific motor movement, within a series of sequential movements, potentially serves as a memory cue for the next step in the assembly. This proposition could explain the negative transfer results found by Barnett, Helbing, Hancock, Heininger and Perrin (2000) or the lack of significant differences reported by Rose, et al. (2002) both of whom used a 3D mouse as the input device to manipulate objects within the VE. Since performances of both tasks are as much physical as they are cognitive, it is possible that the use of the 3D mouse hindered transfer of training for the real-world procedure because the physical movements used to manipulate the parts in the VE were incompatible to those needed to perform the task in the real-world. If the cognitive and psychomotor tasks are associatively linked during acquisition of a complex skill, one could argue that the physical inputs required by the 3D mouse to manipulate parts and tools did not adequately match that of the actual environment, interfering with the learning of the task. More importantly, the 3D mouse may have created incorrect associations due to motor movements that did not match those required by the real-world task, which inhibited transfer or resulted in negative transfer.

Recent theories of learning have placed an emphasis on the environment and its effect on transfer (Greeno, Moore and Smith, 1993). The theory of situated cognition offers an ecological perspective of learning by suggesting that learning is not entirely cognitive, but is also dependent upon social interactions with other individuals in various situations and environments (Greeno, 1989). The meaning, significance, and relationship between objects or people within the environment are learned as one interacts with them. According to this theory, transfer occurs when the affordances and constraints provided within two different environments are similar enough that the person is able to transform one situation to the other.

Constructivism offers an alternative theory suggesting that learning occurs based upon personal experiences. From a constructivist's perspective, the design of the learning environment plays an essential role in how information is communicated to the learner and how s/he integrates that information into their existing knowledge structure. Constructivists recommend that the teaching environment should match that of the operational environment as closely as possible. By replicating the operational environment, memory of the learned skill will be more readily available for use in the operational environment. If the environment, goals, and cognitive processes activated during actual performance are the same as those acquired during training recall, from long-term memory will be more likely (Feltovich, Spiro and Coulson, 1993).

Both of these theories emphasize the importance of the environment although each differs on how closely the environmental elements must match in order for transfer to occur. Applying Gick and Holyoak's theory of transfer (1987), the context of the learning environment need only match that of the performance environment necessary for the trainee to perceive the similarities between the environments.

Skill Acquisition

Most theories of skill acquisition propose that it occurs in distinct phases, which can be identified by qualitative differences in performance (Anderson, 1982; Fitts and Posner, 1967; Rasmussen, 1986). The level of skill acquisition that a person has attained will affect his or her ability to transfer knowledge of that skill to another task. Fitts and Posner (1967) proposed a theory of skill acquisition for psychomotor tasks, which occurs in three sequential phases: cognitive, associative and autonomous. During the cognitive stage a person develops a basic understanding of the task and how it should be performed. The associative stage is marked by improved performance as the learner associates cues in the environment with the appropriate response. Associations are strengthened, modified, or discarded based upon results obtained during practice or training. Successful practice or training will eventually require less cognitive processing leading to the autonomous stage where behavior requires little or no conscious effort. While Fitts and Posner (1967) did not address transfer directly, application of Gick and Holyoak's theory provides some insight as to the requirements for transfer to occur during each stage. Given that only basic information is available during the cognitive stage, learning a new task requires that the training environment should closely match that which the task is to be performed in. As the trainee's skills and knowledge increase, s/he transitions to the associative and autonomous stages, during which training can then become more abstract.

Anderson (1982) developed a theory of cognitive skill acquisition that borrowed heavily from the theory developed by Fitts and Posner for psychomotor tasks. Anderson makes a distinction between two types of knowledge, declarative and procedural, which develop at different stages of learning. Declarative knowledge is defined as a body of facts and general information obtained during initial skill acquisition, similar to Fitts and Possner's cognitive stage. Procedural knowledge consists of skills that a person knows how to perform. Declarative knowledge is converted to procedural knowledge by the process of knowledge compilation, which chunks individual procedures into larger procedures and embeds factual knowledge into the procedures. Performance improves as knowledge compilation occurs through "tuning" which involved the generalization, discrimination, and strengthening of procedures. Singley and Anderson (1989) developed a theory of cognitive transfer which relied heavily on Anderson's ACT* theory of skill acquisition (1989) and strongly adheres to Thorndike's (1901) theory of identical elements where transfer is predicted based upon the number of identical variables, or in Singley and Anderson's (1989) model, shared productions.

Unfortunately, acquisition of a skill does not guarantee that it will always be applied correctly or transferred to another task (Barnett and Kaslowski, 2002). Holyoak (1991) argues that there is a difference between mere skill acquisition and the expertise necessary to transfer a skill to other tasks. Initially the application of a new skill is often context dependent and the person will only apply the skill if the problem is identical, or sufficiently similar to the context in which the task was learned. Only after some level of expertise has been achieved will one be able to transfer knowledge between more diverse subjects. This has important implications for the use of virtual simulators and the level of fidelity required to train a specific task. If the training environment does not help the trainee achieve a particular level expertise, the skills and knowledge gained will not be available for other environments, tasks, or situations.

Simulator Fidelity and Transfer

The issue of simulator fidelity is closely linked to the debate on transfer in that those who subscribe to the theory of identical elements feel that simulators should closely replicate the operational environment while those that believe in a general theory feel that simulators need only be “functionally equivalent” (Hays and Singer, 1989). For complex simulations such as those required to teach aircraft maintenance or surgical procedures, the fidelity of the simulation will be a fundamental factor in determining the amount of transfer.

Fidelity of a simulator is defined as the similarity between the knowledge and skills taught in the simulator to those used in the operational environment. The existing literature regarding the transfer of training suggests that transfer is enhanced when the learning and operational environments are closely matched. However, absolute fidelity is often impractical or impossible to achieve. As such, researchers must be able to define the appropriate level of fidelity necessary to achieve transfer. The precise level of fidelity required for complex tasks is still in question and perhaps the answer may lie more in the level of knowledge that the trainee possesses prior to training (Darken and Banker, 1998).

Waller et al. (1998) described two types of fidelity that play a key role in the transfer of knowledge from VEs to the real world. First is Environmental Fidelity, which is the psychological judgment of similarity between the training environment and the operational environment. Environmental Fidelity defines the level of immersion and is most often referred to as "presence", or the illusion of being part of the virtual environment. Environmental Fidelity is dependent upon the level of realism created by the VE and can be affected by quality of the visual, auditory, and tactile feedback and length of exposure. The second type is Interface Fidelity which is the degree to which the input and output devices used in the training environment are similar to the actions and feedback of the operational environment. Interface fidelity is affected by the ease of interaction and level of user control.

The levels of fidelity required to train a complex assembly task have not yet been identified. For this study we define a complex task as one that requires the integration of cognitive, perceptual, and psychomotor skills. More specifically, the task for this study required participants to learn the spatial relationships and physical interactions between parts as well as the procedural steps and motor movements necessary to properly assemble a 68-piece Lego™ model. While previous studies using VR technologies have explored these concepts individually, few have addressed a complex task, which requires the integration of all of these.

A review of the virtual training literature suggests that different VEs are more appropriate for training different skills. For example, studies involving the training of decision-making have found success with desktop VEs (Pleban et al., 2002) while successful training of motor skills have been shown to require fully immersive environments with stereoscopic HMDs (Rose, 2000).

Training in Virtual Reality

While the bulk of research investigating transfer of training from VEs has involved learning of spatial and motor skills (Stanney, 2002), recent advances in graphical processors and other VR technologies now allow researchers the ability to investigate more complex tasks. The following paragraphs review the empirical literature that addresses the transfer of training from VEs to real-world tasks.

Spatial Navigation: The psychological process of navigation involves extracting visual information from the physical environment as one moves through space (be it physical or virtual) and creating accurate mental representations that can be used for distance estimation, route planning and wayfinding. Researchers are using VR to address how people extract information from the environment and how it is subsequently used for navigation and wayfinding.

Given the visual-spatial nature of VEs it is appropriate that most of the research has been focused on studying the training of spatial orientation and navigation. It is generally accepted (although see Goeger et al., 1998 for an alternative view) that VEs are effective devices for training such skills (see Lathan et al, 2002 for a complete review). Successful training of navigation skills has been demonstrated by several studies (Ruddle, Payne and Dunn, 1999; Waller, Hunt, and Knapp, 1998; Whitmer, Bailey and Knerr, 1995). All of these studies have found some degree of successful transfer using a variety of dependent measures. Perhaps what is most interesting is that trainees seem to have the ability to transfer spatial knowledge from a VE to the real-world task regardless of the input and display device used.

Wilson, Foreman and Tlauka (1997) used an ordinary desktop monitor to train participants to navigate a multi-story building. The VE lacked the fine details of the building but contained important landmarks (i.e., doors, pillars, stairwells, etc.) that existed in the real world. Spatial knowledge was assessed using four measures: 1) pointing to objects not visible from the test site, 2) estimates of Euclidean distance, 3) route distance estimates, and 4) participant's drawings of the building. Results from the pointing test revealed significant improvement for the real-world group and the PC group. It should be noted that both training groups outperformed the control group in all dependent variables; however, interpretation of the results is complicated due to unequal sample sizes. Whitmer et al. (1995) performed a similar study using a HMD coupled with a 3D joystick to train soldiers to navigate a building. Results showed that spatial skills learned in a VE could transfer to real-world navigation tasks provided that the VE provided the appropriate landmarks and cues the participants needed for navigation.

Ruddle, Payne and Jones (1999) compared navigation skills acquired when using a desktop monitor and an HMD from large-scale virtual buildings. Participants assigned to the HMD group used physical head movement and a button box to navigate the environment while participants assigned to the PC group used a mouse and keyboard. Results showed that the HMD group navigated the building more quickly. The authors attribute the differences to an affordance of the HMD, which allows the participant the ability to "look around" more often while traveling through the VE. The HMD group was also more accurate when estimating a linear distance, which most likely attributed to the stereovision provided by the HMD. While the design of this study does not address transfer to a real-world task, the direct comparison between display devices, and perhaps inadvertently between input devices, clearly illustrates the concept that different peripheral devices can create affordances or constraints which in turn affect the trainee's ability to learn.

Waller, Hunt and Knapp (1998) conducted what is perhaps the most thorough study of transfer of spatial knowledge from virtual environments to a real-world navigation task. Their study examined the navigation performance of 125 participants assigned to one of six environments: 1) control group, 2) real-world, 3) Map, 4) VE desktop, 5) HMD with short training exposures (two minutes) and 6) HMD-long, where training exposure was increased (15 minutes). Participants were trained to navigate a 14ft x 18ft maze in their respective environment, which they later performed blindfolded in the real world. The virtual training groups navigated the environment using a joystick with four degrees of freedom. Results of the study showed that all training groups improved but the real-world and VE-long training groups achieved best performance. It is interesting to note that the improvement between the desktop VE and HMD with short exposure is not significant. There was also a significant gender effect for navigation performance in the virtual training groups, which was not found during testing in the real-world environment. It is also worth mentioning that the Guilford Zimmerman standardized test of spatial orientation ability was not predictive of participant's navigation performance.

The results of these studies suggest that navigation skills can transfer to real-world tasks despite control devices that require physical inputs that are incompatible with those required by the real-world task. On the other hand, results from Ruddle et al. (1999) and Waller et al. (1988) suggest that greater compatibility of the visual display device results in improved transfer to real-world performance. Thus, it would seem that when training navigation tasks, environmental fidelity is more important than interface fidelity.

Motor Skills: Another area in which the applications of VEs are being explored is motor learning, specifically in the arena of vision-action research. Despite results from an early study that showed no significant transfer of motor skills (Kozak, Hancock, Arthur and Chrysler, 1993), subsequent research has shown a reliable positive transfer of motor learning from VEs to the real world (Kenyon and Afenya, 1995; Rose, et al., 2000).

Kozak and colleagues (1993) were one of the first to explore the transfer of motor skills from a VE to the real-world task. Participants were trained to perform a pick and place task, which required participants to pick up and move virtual objects (soda cans) and place them as accurately as possible on a target in a specific order. The immersive virtual environment replicated the real-world task and was displayed using an HMD. Hand movements were recorded using a DataGlove™ equipped with an electromagnetic position sensor. Twenty-one participants were assigned to one of three groups: real-world training, VR training, and a control group. Performance was determined using average task completion times of 30 trials. The results showed that no transfer occurred from the VE to the real-world task. However, the methodology used has been questioned (see Durlach and Mavor, 1995) and the results have since been disputed (Kenyon and Afenya, 1995)

Kenyon and Afenya (1995) replicated the Kozak et al. (1993) study using a projective CAVE environment in lieu of an HMD, arguing that insufficient spatial mapping between the VE and the real world led to the results reported by Kozak et al. (1993). Kenyon and

Afenya (1995) found a small but significant training effect for participants assigned to the virtual training group. The results of the study also point to some of the technical challenges that affect transfer of motor learning to real-world tasks. For example, peak movement velocities for participants in the virtual training group were almost half of those in the real-world training group. Similar results reported by Graham and MacKenzie (1996) found that the secondary movement phase was twice as slow when pointing in a virtual environment. These differences help explain the slower performances of the VR training groups in both studies. Interestingly, the slower performance in the VE does not seem to affect subsequent performance in the real world. Kenyon and Afenya (1995) attribute the differences to the lack of haptic feedback and the delay that occurs between the actual physical movement and the subsequent movement of the cursor or virtual manipulator.

Rose et al., (2000) found positive transfer for a simple sensorimotor task where participants were required to manipulate a virtual ring along a curved path without contacting the ring to the curve. Participants in the virtual training group viewed the VE through a stereoscopic HMD and manipulated the virtual ring using a 3D mouse. Results showed significantly lower error rates for the virtual-training group over the control group, which received no training. There was no significant difference between the virtual group and the real-world training group.

Using the testing paradigm described above, Rose et al. (2000) conducted two follow-on studies in an effort to understand the differences in cognitive demand between the virtual- and real-world training groups. In Experiment 2, Rose et al. (2000) added a secondary motor task of tapping Morse code. In Experiment 3, a secondary cognitive task required participants to recall target colors and auditory tones observed while performing the steadiness task. Surprisingly the results of the studies found that the participants that received training in the VE were less affected by the secondary motor task while no significant differences between training groups was found for the cognitive task. Rose et al. (2000) argue that the lower interference may result in cognitive processes that are more automatic than those trained in the real-world environment. Regarding models of skill acquisition, the results from Rose et al., (2000) suggest that VR allows a greater level of skill acquisition regardless of the amount of transfer that occurs.

Todorov, Shadmehr and Bizzi (1997), have evaluated the use of a desktop VE application to achieve a specific motor movement using augmented feedback provided within a VE. They showed that hitting a ping-pong ball to a specific target could be improved by having participants replicate the actions of a virtual paddle, which demonstrated the desired trajectory. Participants trained to perform the task in the VE significantly outperformed the control group (pilot studies showed no difference between the control group and real-world training group).

The results from these studies suggest that more complex tasks, which integrate visual stimuli with motor actions, require a greater degree of environmental and interface fidelity. Werkoven and Groen (1998) studied the individual affects of manipulating objects in VEs using different input devices under monoscopic and stereoscopic viewing conditions. Their results showed that speed and accuracy of the manipulations were faster and more accurate when using stereoscopic displays. In addition, control of a virtual hand using a motion-tracking device was significantly faster than using a 3D mouse regardless of the display type. Ware and Balakrishnan (1994) demonstrated that even small lag rates (200ms) between the actual movement and the response shown in the VE can lead to considerable degradation of performance in reaching tasks.

Physical Rehabilitation: The results of Todorov et al., (1997) and Rose et al. (2000) suggest that VR may be applicable for physical rehabilitation applications by allowing patients the ability to practice psychomotor movements in VR with less perceived cognitive demand. Researchers have found success in using VEs to retrain psychomotor ability in patients after a stroke or traumatic brain injuries. Holden, Todorov, Callahan and Bizzi (1999) applied Todorov et al.'s, (1997) original methodology to rehabilitate the range of motion of two stroke patients with upper extremity paresis. Researchers designed a VE that used an HMD to replicate a real-world task that forced the participants to exercise their impaired limb. It was important that the VE replicated a real-world task as many patients fail to apply coping skills taught during traditional rehabilitation exercises to real-world tasks (Holden and Todorov, 2000). Using a "teacher trajectory" similar to that used by Todorov et al., (1997) two participants practiced extending their arms and placing a virtual envelope into a virtual mailbox slot. Both subjects received 16 treatment sessions of 1 to 2 hours. After training in the VE, both subjects performed the task in the real world. Both subjects improved reach by 18cm and 9cm respectively, representing a 50% reduction in error and 25% improvement in reach excursion.

Results similar to Todorov et al., (1997) and Holden et al., (1999) have been reported when using VR to rehabilitate the power and endurance of patients' ankles and hands after a stroke. Boian et al., (2002) developed a desktop VE, which required patients to manipulate a virtual airplane or boat using their ankle as a haptic joystick. Results from preliminary clinical trials showed that the exercises transferred to an increase in walking speed and endurance. Boian et al., (2002) have also increased range of motion of the thumb, finger speed and finger dexterity using a similar device for hand rehabilitation.

Cognitive Tasks: Successful training in VEs has also been demonstrated for cognitive skills. Pleban et al., (2002) demonstrated that VEs could be used to improve decision-making skills of platoon leaders. After four training sessions in virtual combat simulations both experienced and inexperienced platoon leaders demonstrated improved decision making skills within urban combat environments. Other studies have found positive transfer for procedural tasks including naval maneuvers (Magee, 1997) surgical procedures (Taffinder and Sutton et al., 1998), repair of the Hubble Telescope (Loftin and Savely et al., 1997) and simulated missile launches (Regian, 1997).

Other interesting applications include the use of VEs to train interactions between humans. Hubal and Frank (2002) used virtual humans modeled with realistic behaviors to teach law enforcement officers non-violent conflict resolution skills. Virtual characters, or “avatars,” are also being used to train human interaction skills such as practitioner-patient interviewing skills. Simulated patients have also been used to teach medical students how to perform patient assessments (Hubal and Frank, 2001).

Despite the positive results of the studies described above, successful transfer from VEs has not been observed in all studies. Arnold and collegues (Arnold and Farrell, 2002; Arnold, Farrell, Pettifier and West, 2002) argue that training in VEs is inherently more difficult regardless of the amount of transfer that is achieved especially in the case of complex tasks that require both cognitive and motor skills. A series of studies performed by Barnett and Helbing et al., (2000), evaluated the training effectiveness of VEs for the removal and replacement of an aircraft fuel valve in an immersive VE. Results of these studies showed that training in an immersive environment resulted in longer training time and decreased subsequent performance when compared to another computer-based training device. It should be noted however, that Barnett et al., (2000) provided only one training session on the task prior to testing. Evidence from Waller et al., (1998) suggests that learning within VEs increases during later trials while those receiving training in the real world learn most in the early trials.

Further evidence that a lack of interface and environment fidelity can hinder transfer can be found in the literature regarding PC-based Aviation Training Devices (PCATDs). PCATD are low fidelity flight simulators that can be operated with a personal computer. Typically the flying environment and instrument panel are depicted on the computer screen while the airplane is controlled with the use of a joystick and keyboard or generic control panel.

Research has shown that the use of PCATDs are effective for specific pilot training applications but fail to effectively reduce necessary training time in the actual airplane. An investigation of transfer of training by Taylor et al., (1999) found that 10 hours of PCATD training was equivalent to 1.5 hours of real-world flight training. Results also showed that most of the benefits of using PCTADs occurred in the early stages of the training program. Several PCATD studies report positive transfer of training effects for instrument maneuvers that entail procedural components but not for flight tasks that require perceptual-motor skills (Taylor et al., 2003; Taylor et al., 1999). These findings suggest that the low interface fidelity of PCATD's makes them less effective in training of the “Physical Airplane” or the “stick and rudder” aspect of flying (Dennis and Harris, 1998).

The implication of these findings is that transfer of complex task training is more sensitive to deficiencies in environmental than interface fidelity. However, the role of interface fidelity in transfer of training from VEs to complex real-world tasks, such as the assembly task described by Barnett et al., (2000) has yet to be examined. In addition, the applicability of immersed and desktop VEs for training complex tasks has yet to be directly assessed. This study is specifically interested in the effect of environmental and interface fidelity on the transfer of training of a complex task such as manual assembly.

Individual Differences

It has been argued that individual differences account for more performance variability in VEs than system design factors (Kaber, Draper and Usher, 2000). There are several individual differences that have been shown to influence the effectiveness of computer-based training including cognitive ability, cognitive style, gender, and age (Chen, Czerwinski and Macredie, 2000; Cutmore et al., 2000), which suggests that these same factors will play a role in the effectiveness of training in VEs.

Spatial Aptitude: Perhaps one of the most important individual differences found to influence learning in VEs is that of spatial aptitude. Spatial aptitude is the ability to judge how a given object would look from another perspective and has been shown to play a key role in predicting one’s performance in navigating real-world environments (Thorndyke and Hayes-Roth, 1982) and information retrieval from menu structures which is considered a spatial memory task (Borgman, 1989). Spatial aptitude has also been shown to predict navigation performance in several studies that measured participant's ability to navigate a virtual maze (Moffat, Zonderman and Resnick, 2001; Cutmore et al., 2000;).

Gender: Gender has been strongly correlated to spatial ability (see Voyer, Voyer, and Bryden, 1995). As such, gender differences have been shown to play a role in performance on tasks such as mental rotation and spatial perception. The same results have also been found in transfer of training from VEs. Waller et al. (1998) reported an effect for gender while using VEs as a training tool and admitted to being "surprised to find such robust differences between men and women." (p. 142). In their study, men who trained in a VE significantly outperformed women trained in the same VE. In a follow-up study, Waller (2000) found that the performance differences were related to interface proficiency and spatial aptitude. Cutmore et al., (2000) also reported finding a significant effect of gender while learning to navigate a virtual maze. Cutmore et al., (2000) conducted a follow-on study that controlled for gender differences and found that females with higher visual-spatial ability outperformed females with low visual-spatial ability, as determined by scores obtained from the WAIS-R block design test.

Computer Self-Efficacy: Gender differences with regard to self-efficacy are also very important in human-computer interaction and the application of computer-based education. Studies investigating the role of self-efficacy, or one's perceived abilities, have been shown to effectively predict the user's ability to learn and perform a particular task (Torkzadeh, Pflughoeft and Hall, 1999). In particular, the belief that one has the ability to perform a task increases the likelihood that the person will successfully complete the task (Eachus and Cassidy, 1997). Bandura (1980) proposes that self-efficacy emerges during the acquisition of cognitive, physical, and social skills. The success or failure experienced during the acquisition of these skills affects one's beliefs about their capabilities to perform similar skills or acquire new knowledge. Bandura (1997) describe three factors that influence self-efficacy, which include magnitude, strength, and generality. Generality is the degree to which the expectation is generalized across situations which has implications for the transfer of training.

Research regarding self-efficacy and HCI has shown that computer self-efficacy is critical to the success of computer-based learning (Torkzadeh, et al., 1999) and may mediate gender effects such as those cited above. Chen (1986) found that when the quantity of computer experience was controlled, differences in attitudes and interest associated with gender were not significant. These results are consistent with reports that found that prior computer exposure influenced attitudes and anxiety towards computers more than gender (Massoud, 1991: Badagliacco, 1990). Cassidy and Eachus (1997) suggest it is the quality of the computer user's experience rather than quantity of experiences based upon their discovery of a disassociation between computer self-efficacy and a measure of computer familiarity.

While self-efficacy has been shown to predict performance in numerous tasks it has also been shown to be domain-specific (Bandura et al. 1980). A common example is of a person with a high level of self-efficacy in playing a sport may have a low level of self-efficacy in learning math or vice-versa. However, there is little research investigating the generality of self-efficacy between similar tasks or environments. For example, does one's level of self-efficacy in mathematics generalize to self-efficacy in engineering? More appropriately, does a user's level of computer self-efficacy predict successful interaction with a VE or perhaps influence transfer of training from a VE? This idea has yet to be empirically tested.

The effect of individual differences has yet to be examined for transfer of training for more complex tasks such as manual assembly. This study will explore the role of individual differences on transfer of training from a VE to the real world.

Conclusion

While there is a great deal of research evaluating the use of VEs for transfer of training for navigation tasks, psychomotor skills, and physical rehabilitation, there is little research that investigates the transfer of a complex manual assembly task. The primary purpose of this study is to determine if participants can transfer learning of a complex task in a virtual environment to the real world.

The interpretation of existing research is complicated by the use of different types of VR technologies that afford varying degrees of environmental and interface fidelity. A secondary goal of the current study is to determine if any of these environments provide a clear advantage in learning and transferring skills to the real world. The results will help provide a better understanding of the level of environmental and interface fidelity necessary to train a complex task

With few exceptions, the effect of individual differences has yet to be examined for transfer of training from VE. The current study will explore a variety of individual differences known to affect HCI and their potential effect on transfer of training from VEs.

CHAPTER 2

METHOD

Participants

All participants were asked to complete a demographic questionnaire and sign an informed consent agreement prior to data collection. Given the novelty of the training task it was important to determine a distribution of performance on the Lego™ assembly task. In order to gather a reliable distribution, ninety-eight college students participated in the Pre-test. Assembly times ranged from 5.1 minutes to 32.9 minutes. Outliers in the distribution, defined as greater than three standard deviations from the mean were not considered for participation in the training study.

Because of the vast differences in assembly times recorded during the Pre-test, it was decided that the participants would be divided into two groups: Fast Builders (FB) and Slow Builders (SB). Assignment to a Building Group was determined using a median split of the participants' Pre-test times (Median = 17.5 minutes). Average assembly time for FB was 13.96 minutes (SD = 1.72) while average assembly time for SB was 21.21 minutes (SD = 3.17).

A chi-square analysis of Pre-test assembly times revealed no significant effect for Gender. As such, participants were assigned to their respective building group solely upon their time to complete the Pre-test.

The 48 participants (27 female and 21 male) were grouped and assigned to one of four training environments: full immersive VE (HMD), PC-Based VE (PC), Real-world training (RW) and a control group which received no training (NT). Each group consisted of 6 FB and 6 SB. Participants were assigned to a training environment such that the average assembly time for each environment was not significantly different (see Table 1).

		NT		RW		PC		HMD	
		Slow	Fast	Slow	Fast	Slow	Fast	Slow	Fast
NT	Slow		.001	.879	.001	.922	.001	.788	.001
	Fast			.001	.888	.001	.743	.002	.770
RW	Slow				.001	.803	.001	.711	.001
	Fast					.001	.818	.001	.849
PC	Slow						.001	.843	.001
	Fast							.001	.957
HMD	Slow								.001
	Fast								

Table 1. P-values obtained from post-hoc analysis of Pre-test assembly times by Training Environment and Building Group

Apparatus

The pre- and post-tests required the assembly of a Lego™ model of a forklift consisting of 68 pieces. Instructions for building the forklift were pictorial in nature consisting of 35 individual assembly steps. A second Lego™ model of a racecar was used for the post-training transfer of learning test. The racecar consisted of the same parts as the forklift assembled in a different order and configuration. Instructions for the racecar consisted of 37 assembly steps.

Digital models of the individual Lego™ parts were created using LDraw, which is computer-aided drafting software for designing virtual Lego models. The geometry created in LDraw was converted to VRML 2.0 data and imported into Division Reality's Digital Mockup 2000i software. The virtual training environment for this study was created at the Virtual Reality Center at the National Institute for Aviation Research at Wichita State University.

The Fully Immersed VE (HMD) training group viewed the environment using a NVIS nVisorSX HMD at 1280 x 1024 resolution with 60 degrees of diagonal viewing angle and a constant screen refresh rate of 30Hz per eye. Because of limitations to the head-mounted display, participants assigned to the HMD training environment were required to have a minimum of 20/60 uncorrected vision or have 20/20 corrected vision with contact lenses. Participants who indicated they were prone to motion sickness on the demographic questionnaire were not assigned to the HMD environment (see appendix A).

The environment was generated using an SGI Onyx300 equipped with two graphical outputs (IR4 pipes), 8 CPUs and a 8GB Digital Audio graphics card. Motion tracking of the head and hands was accomplished using an Ascension Flock of Birds magnetic motion tracking system with 3 sensors; one on each hand and one on the head (see Figure 1).

Figure 1. HMD and pinch gloves with motion tracking sensor attached.

Object manipulation was accomplished using Fakespace's pinch gloves equipped with electromagnetic motion transmitters. The VE allowed the participant to select, manipulate and assemble the virtual model. The assembly instructions provided with the Lego model were digitized and displayed sequentially on a virtual billboard located within the VE. Participants could advance or review the instructions using prescribed hand gestures (see Table 2).

Finger	Right Hand	Left Hand
Index	Select Part	Reset Position
Middle	Move Forward	Move Backward
Third	Orbit Right	Orbit Left
Fourth	Page Instructions Forward	Page Instructions Back

Table 2. Hand gestures used to navigate the environment and manipulate the parts

The PC-based VE (PC) training group viewed the environment on a 21" desktop monitor. The screen was configured to display the VE at 1152x864 pixels with an 80Hz refresh rate. Participants used a keyboard and three-button mouse to interact with the software. The VE was generated using an IBM Intellistation M-Pro equipped with a 3.2 GHz Pentium 4 processor and an NVidia FX1500 Video Card.

In an effort to identify individual differences which may affect the transfer of training of cognitive skills from VEs to the real-world, participants completed three cognitive tests including: the Wonderlich Personnel Test (WPT) of general intelligence, the Computer User Self-Efficacy Scale (CUSE), and the Mental Rotations Test (MRT) to measure spatial aptitude. All three tests were administered after training.

The WPT is a 50-item multiple choice measure of general intelligence. It was chosen due to its ability to be administered relatively quickly (12 minutes) and has high correlation with more formal intelligence tests such as the WAIS-R ($r = 0.92$). Test-retest reliabilities have ranged from 0.82 to 0.94 (Hawkins, Faraone, Pepple and Seidman, 1990).

The CUSE is a 30-item questionnaire measuring computer user self-efficacy. CUSE is the only measure of computer user self-efficacy to be validated with reliable internal and external factors. Results show a high test-retest reliability (r = 0.97) and high construct validity (r = 0.75) (Cassody and Eachus, 1997).

The Mental Rotations Test (Vandenberg and Kuse, 1978) measures spatial aptitude. Participants are given 10 minutes to answer up to 20 questions where they must compare a criterion figure to four alternative figures. Two of the alternative figures are the same as the criterion figure except they have been rotated. Subjects must distinguish the correct alternatives from the two distracters. Evaluations by Vandenberg and Kuse (1978) show a high test-retest reliability (r = 0.88) and high construct validity (r = 0.86).

Procedure

Pre-test: After completing the informed consent and demographic questionnaire, participants were required to assemble the Lego^{TM} forklift as quickly and accurately as possible. The parts required to assemble the model were grouped and arranged by shape, color and size. Participants were directed to use the assembly manual, which was provided with the Lego model, was placed in front of the participant at the beginning of the task; however, the participant was free to relocate the instructions if they desired. The area directly in front of the participant was left clear of any parts to allow enough workspace to assemble the model. The experimenter recorded the participant's time to assemble the forklift, which started when the instruction booklet was opened and stopped when the last part was attached.

Training: All participants (except control) received four training sessions over a period of four days. Each training session consisted of the participant successfully completing the assembly of the forklift one time in their assigned environment. During training participants were asked to complete the assembly as quickly and as accurately as possible. Time required to complete each training session was recorded for later analysis.

Participants assigned to the real-world training group (RW) assembled the actual Lego™ forklift essentially repeating the Pre-test task for four additional days. The control group (NT) received no training prior to being tested 5 days later.

Participants assigned to the HMD training environment were instructed how to use the pinch gloves to navigate the VE, manipulate the parts, and page through the instructions. After their initial instruction participants were outfitted with the pinch gloves and were allowed to practice navigating and manipulating the VE prior to donning the HMD. This practice time was not recorded as part of the training time. When the participant indicated s/he was confident with the pinch glove controls the experimenter conducted an informal performance test that required the participant to use the pinch gloves to correctly respond to the experimenter's commands. After the participant passed the performance test the gloves were removed so s/he could don the HMD and make the necessary adjustments for visual acuity and intraocular distance. After the HMD was properly adjusted the participant put on the pinch gloves and the virtual environment was reset. The experimenter began recording assembly time upon acquisition of the first part and stopped when the last part was assembled.

Navigation within the HMD environment was achieved using either physical movement (i.e., moving around the room) or through the use of hand gestures. Both options were available to each participant. Participants were taught eight hand gestures, which allowed them to "fly" through the environment by touching various fingers to their thumb.

Manipulation of the virtual parts was also achieved using hand gestures inputted using the pinch gloves. To select a part, the participant moved his/her virtual hand to collide with the virtual part. When a participant's hand collided with a part, the part's color turned red and an auditory "clunk" sound was triggered. Participants selected or "grabbed" the part by touching the right thumb to the right index finger. The participant could then drag the part through the VE by maintaining the hand gesture and moving his/her hand. The part could be rotated and oriented by making the necessary hand movement required to achieve the desired position. When the participant released the hand gesture the part was released.

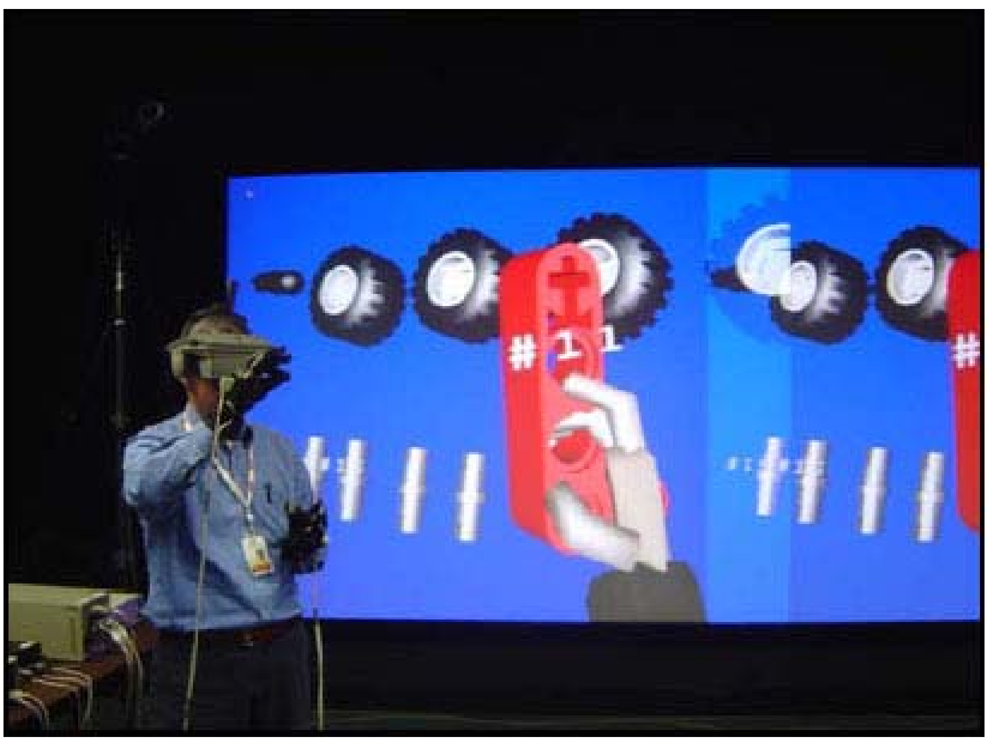

Figure 2. A participant in the HMD Environment manipulates a virtual part. The participant's view of the environment can be seen on the screen in the background.

Participants in the PC training group assembled the model using a desktop computer with a keyboard and three-button mouse. Navigation through the VE and manipulation of the parts was achieved using the mouse in combination with function-keys on the keyboard (see Appendix B). Participants received a demonstration showing how to navigate and manipulate the environments. After the demonstration participants were allowed to practice each of the manipulations. When the participant indicated s/he was confident with the manipulations the experimenter conducted an informal performance test that required the participant to correctly respond to the experimenter's commands. After the participant passed the performance test the environment was reset. The experimenter began recording assembly time upon acquisition of the first part and stopped when the last part was assembled.

The arrangement of the VE was exactly the same for both virtual training groups. The virtual Lego™ parts were grouped and arranged exactly as they were in the Pre-test; however, the parts were located on the right-hand side of the participant. The model was assembled in the center of the environment. The assembly instructions were digitalized and placed on a two-dimensional virtual billboard located at the left-hand side of the VE (see Figure 1). The virtual billboard was programmed so that the surface of the billboard was always perpendicular to the participant's viewing angle. That is, as the participant moved through the environment the billboard rotated so that the instructions were always facing the participant.

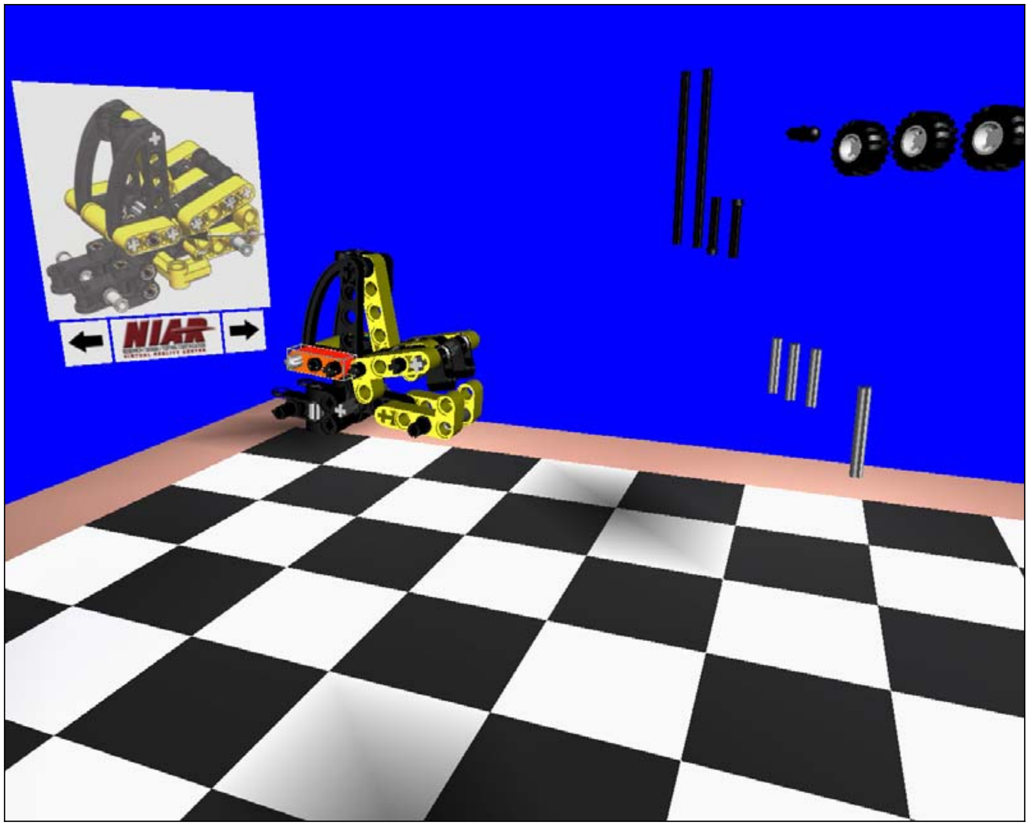

Figure 3. Screenshot of the PC Environment

Post test: All participants completed the three cognitive tests and performed two manual assembly tests: post training test which required assembly of the forklift and a transfer of learning test which required assembly of a Lego™ racecar. The racecar consisted of the same parts as the forklift assembled in a different order and configuration. The individual parts were laid out on a desk in the same arrangement that was used in the Pre-test and the virtual environment. Both tests required participants to correctly assemble the model as quickly as possible. The learning test was always administered after the Post-training test.

Important Differences between Virtual and Real-world Training Environments

It is important to note that despite the advances of virtual reality technologies there are currently several technological constraints that prevent VEs from precisely replicating real-world environments. These constraints are limitations to both environmental and interface fidelities described by Waller (1998). These constraints create key differences between the real-world training and the virtual training environments. These differences are described below.

Scale of Parts: The geometry for the virtual parts was originally drawn to full scale. However, pilot testing revealed that the parts were too small to be manipulated with the virtual hands used in the HMD environment. The most noticeable problem with the original size of the parts was that the virtual hand would occlude the part making it difficult for the participant to select, move, and orient the part. As such the scale of the parts was increased 1.5 times their normal size. The increased size of the parts may offer advantages to those who trained in the virtual environments. One advantage to the bigger parts would come in the form of Fitts' Law (1954). The larger parts in affect create a larger target to acquire thereby decreasing the index of difficulty to acquire that target. The larger targets may also make the parts more salient. Thus, features that distinguish similar parts may be more salient to those in the virtual environments. This could potentially minimize the selection of wrong parts.

Part specificity: The model used for this particular study contained 68 parts but only 25 unique parts, meaning that were multiples of several parts (i.e., there were four wheels, nine axles etc.). When assembling the real-world model the participant can select from any of the repetitive parts relies on physical constraints which either allows or prevents parts to be attached to one another (i.e., wheels can be placed interchangeably at any of the wheel axels). However, in the virtual environment the constraints or "behaviors" for each part must be programmed specifically for each individual piece. For this particular VE the constraints for the virtual parts are coordinate-based. That is, each part can only be placed in a specific location within and three-dimensional Cartesian coordinate system. As such, each piece becomes unique. So while two parts may be geometrically identical, their behavioral constraints are different. The result for the trainee is that parts are no longer interchangeable (i.e., each wheel must be placed at a specific location). To accommodate this change we assigned each virtual part a number. Corresponding parts in the assembly booklet were also numbered. In the virtual environment the part numbers would appear as the participant's virtual hand contacted the part. Likewise, the part numbers would disappear when the virtual hand no longer contacted the part. Hypothetically this change could have an advantageous or disadvantageous affect depending on how the participant chose to adapt to the change. On one hand, (no pun intended) the part number essentially eliminates the need to use the assembly instructions as the participant could choose to search for the next part based strictly upon their part numbers. On the other hand, the situation increases the memory demand for the assembly task as it essentially forces the participant to play a virtual game of "Concentration" as they search through identical looking parts for the correct part number.

Snap-to Function: The coordinate-based constraint system requires that the part be placed at a precise location in the coordinate system. Because this requires an unrealistic level of accuracy (up to .0001 inches) for users a "snap-to" function was employed to help participants locate parts it its precise location. With the snap-to function, participants were only required to place a part within a boundary of its actual location for it to be placed properly. If the part to be assembled contacted one of the other parts on the assembly, the snap-to function would place the part in the correct location with the correct orientation. This feature had the potential of being abused by participants since they could simply select a random part, collide it with another, and both parts would snap into place on the assembly. The result would lead to unrealistic assembly times and more importantly, prevent the transfer of training. To prevent this, the experimenter enforced a strict rule with regards to assembly of the virtual models. Simply stated, participants were required to select and assemble parts individually. If parts inadvertently contacted each other (thereby automatically snapping into place), the experimenter replaced the part to its original location in the parts layout.

Manipulation of virtual parts: The snap-to function is a symptom of one of VR's shortcomings, which is that fine motor movements are extremely difficult to replicate in VR, especially without haptic feedback. Specific to this simulation, the motion capture of individual finger movements was not possible. Thus small movements that could normally be made with relatively small finger movements required they be made with the entire hand. Without the ability to replicate fine motor movements users are forced to locate the parts using somewhat exaggerated motor movements. That is, instead of being able to position and connect a part with their fingers, a participant was required to move their entire hand or in some instances their entire arm. While there are devices that can input the motor movement of a user's fingers (i.e., Immersion Corp.'s CyberGlove), the challenges to make such a device perform realistically are quite considerable. The affect of this limitation has two potential affects. First, the inability to replicate the fine motor movements of the fingers forces the recruitment of larger muscle groups potentially increasing the level of physical fatigue experienced by the users. Second, the larger muscle groups lack the accuracy of the smaller muscle groups. Adapting the larger muscle groups to perform such tasks could potentially increase training time.

In addition, the act of selecting a desired part in the VE was somewhat more difficult than obtaining the part in the real world. In order to select a part, the participant had to contact the part with their virtual hand, which changed the color of the part to red. While the part was selected the participant was to make a specific hand gesture to manipulate the part. Even though the hand gesture was somewhat natural (pinching the right index finger to the right thumb) participants did require practice to use the correct gesture.

Navigating within VEs: The size of the virtual parts as well as the inability to capture fine motor movements influences how participants navigate through the VE. In the real-world task very little movement is required beyond reaching for a new piece. However, due to the inability to replicate fine motor movements body movements within a VE must be exaggerated. Specifically, when a new piece is to be selected, the participant may need to "fly" towards it in order to reach it. Flying through the VE requires the participant to learn a series of hand gestures (see Table 1) in order to move forward, backward, left, right, etc. In the real world this task requires very little conscious effort; however, in the VE participants must remember a specific sequence of hand gestures required to perform the desired movements.

Much like the act of selecting a part, participants found that navigating the VE required a certain amount of practice to learn. Natural motion, (i.e. walking towards or away from a part) was somewhat limited by the use of a magnetic motion tracking system. Participant's distance of movement from the motion sensor was minimized so that they remained within the sensor's magnetic field (approximately 10 feet). In addition participants were tethered to the motion tracker and HMD by electrical wires, which were connected to their respective control boxes. These wires further limited participant's movements and range of motion.

Physiological issues: It is well documented that immersion into VE environments can cause a certain amount of physiological discomfort (Harm, 2000; Lawson et al., 2000; Viirre and Bush, 2000; Welch, 2000). Symptoms include nausea, dizziness, vertigo, headache, claustrophobia, and others. While there are several ways to minimize the occurrence of these symptoms they are not entirely preventable. Obviously one would expect the occurrence of the symptoms listed above to interfere with any learning that may occur within the VE. We attempted to minimize the possibility of the participants experiencing discomfort by maintaining a constant frame refresh rate of 30Hz.

Quantifying Transfer

Several formulas have been used to measure transfer of training (Gagne, 1948). Most of the studies, including those cited previously, employ one of two formulas. The first simply measures the difference between the pre- and post-training training performance by subtracting the post-training performance from the pre-training performance. The second formula calculates a ratio of improvement for a training group over that of a control group as shown:

$$\text{Percent of Improvement: } \frac{C - T}{C} \times 100 \qquad (2.1)$$

Where C represents the mean assembly time for the control group. T is the mean assembly time for the treatment group. Gagne (1948) points out that this formula is strictly dependent upon the raw data and thus does little more than offer a measure of improvement for a specific task. Generalization of the results from a study using this formula is limited to equivalent tasks. That is, transfer obtained from an experiment yielding the results 12-10/10 will show the same amount of transfer as another study yielding the value 24-10/20. While both studies show a 20 percent improvement there are large differences in the amount of change between the two experiments, the meaning of which is ambiguous (Gagne, 1948).

The use of raw data alone only allows a measure of improvement; it does not allow one to directly determine the amount of learning that is achieved between studies which use different tasks. This is an important consideration when comparing transfer from different VE's, as each environment will be somewhat different from the others in order to accommodate the various input and output devices that are used. As such, each VE should be treated as a separate training task.

To prevent these differences from masking or exaggerating the affects of different training environments, a formula is needed that allows comparison of transfer percentage found on one task to that of another. This is achieved by dividing the difference between the Treatment Group's final score (T_{post}) and the Control Group's initial score (C_{pre}) by the improvement obtained by the control group where C_{post} is the final score of the control group.

$$\text{Percent Group Transfer: } \frac{C_{pre} - T_{post}}{C_{pre} - C_{post}} \text{ X } 100 \qquad (2.2)$$

The formula for Percent Group Transfer, as it is shown above, allows one to measure the amount of learning that occurs for a particular treatment group. A slight modification of the formula allows a measure of learning for the individual trainee by substituting the Treatment Group's Final Score with the individual's final score where I_{post} is the final score of an individual in a treatment group.

$$\text{Percent Individual Transfer: } \frac{C_{pre} - I_{post}}{C_{pre} - C_{post}} \text{ X } 100 \qquad (2.3)$$

In addition to quantifying percent of transfer it is also necessary to determine the efficiency of the training environment. There are two paradigms for measuring transfer. The first is to train all treatment groups to a desired criterion. Using this paradigm the number of trials is the dependent measure as the trainee performs as many training trials as necessary to achieve a desired level of performance. The alternative method is to hold the training trials constant and measure the difference in performance after training. When the number of training trials is held constant it may be possible for trainees from different treatment groups to achieve equal levels of performance but the amount of time required to achieve equivalent levels may vary. Thus it becomes necessary to determine the efficiency of each training environment as a function of training time. This is calculated using a ratio of improvement over training time. The difference between C_{pre} and T_{post} is divided by the total training time ($T_1 + T_2 + T_3 + T_4$) as such:

$$\text{Training Efficiency} = \frac{C_{pre} - T_{post}}{\sum (T_{1-4})} \qquad (2.4)$$

The use of all three formulas provides a comprehensive view of the training effectiveness for the different training environments. Slight modification of each of the formulas can be used to measure the amount of learning that transfers to a new task by substituting the assembly times of the learning task (L_{post}) for the assembly times of the transfer task (T_{post}) as such:

$$\text{Percent Individual Learning} = \frac{C_{pre} - L_{post}}{C_{pre} - C_{post}} \text{ X } 100 \qquad (2.5)$$

Hypothetical Solutions

Given that the study makes the distinction between transfer of training and transfer of learning, there are several hypothetical outcomes that could occur. Descriptions of these outcomes along with theoretical explanations for the results are described below.

Positive Transfer/ Positive Learning: This is obviously the most desired outcome, as it would demonstrate that training method is effective and the learned skills transfer to a new task or environment. Using time on task as a dependent variable a High Transfer/ High Learning condition occurs when time to complete the training test (T_{post}) and the learning test (L_{post}) are lower for the training group than those achieved by the control group.

Positive Transfer/Negative Learning: This condition would indicate that the training method is effective but the skills learned do not transfer to a new task or environment. When time on task is the dependent variable a High Transfer/Low Learning condition occurs when time to complete the training test is lower for the training group (T_{post}) than those achieved by the control group (C_{post}) but time to complete the learning test (L_{post}) is greater than that achieved by the control group.

Negative Transfer/Positive Learning: This would be a most unlikely condition in that it would indicate that the training method is poor but the learned skills are nonetheless still transferred to a new task or environment. When time on task is the dependent variable a Low Transfer/High Learning condition occurs when time to complete the training test is lower for the control group (C_{post}) than those achieved by the training group (T_{post}) but time to complete the learning test (L_{post}) is less than that achieved by the control group.

Negative Transfer/Negative Learning: This would be the least desirable outcome, as it would indicate that the training method is not effective and the learned skills do not transfer to a new task or environment. Low Transfer/Low Learning condition occurs when time to complete the training test and learning tests are lower for the control group than those achieved by the training group (T_{post} and L_{post} respectively).

It is hypothesized that positive transfer will be found for both the training and learning tasks for all training environments and building groups but that efficiency will be lower for the virtual training groups.

CHAPTER 3

RESULTS

Data Screening

Prior to statistical analyses the results for each dependent variable were screened for outliers, defined as any data point greater than three standard deviations from the mean for the dependant variable within each training environment and building group. In order to maintain equal sample sizes per group all outliers were replaced with an extreme value that was not outlier. Tabachnick and Fidell (1996) recommend this technique for maintaining the affect of the extreme score but limiting the impact upon the distribution.

Training Task Improvement

Improvement on the Training Test was calculated for each participant by subtracting their Post-training assembly time from their Pre-test assembly time. Individual improvement scores were subjected to 2x4 between-subjects ANOVA.

Results showed a significant main effect for Training Environment $F\,(3, 40) = 9.65$, $p < .001$, partial $\eta^2 = .420$, $1\text{-}\beta = .995$. Post-hoc analysis (Tukey's HSD) revealed that the RW training group improved significantly more than all other groups (see Figure 4). Although there was no significant difference between the PC and HMD groups, they both improved significantly more than the control group. The relationship between pre- and post training assembly times are shown in Figure 5.

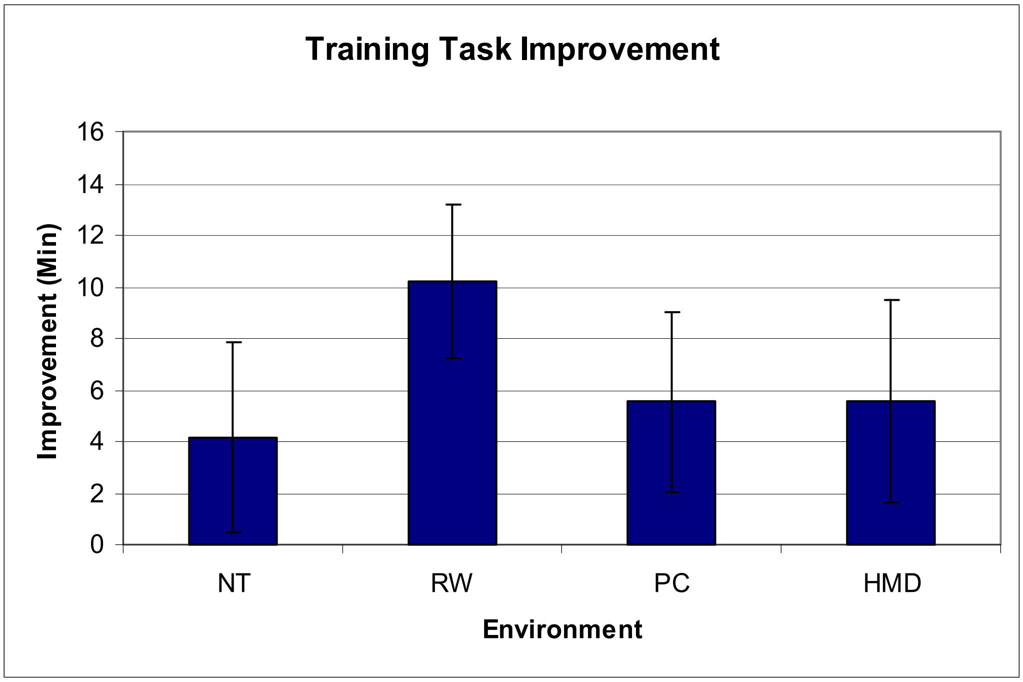

Figure 4. Mean improvement time and standard deviations by Training Environment

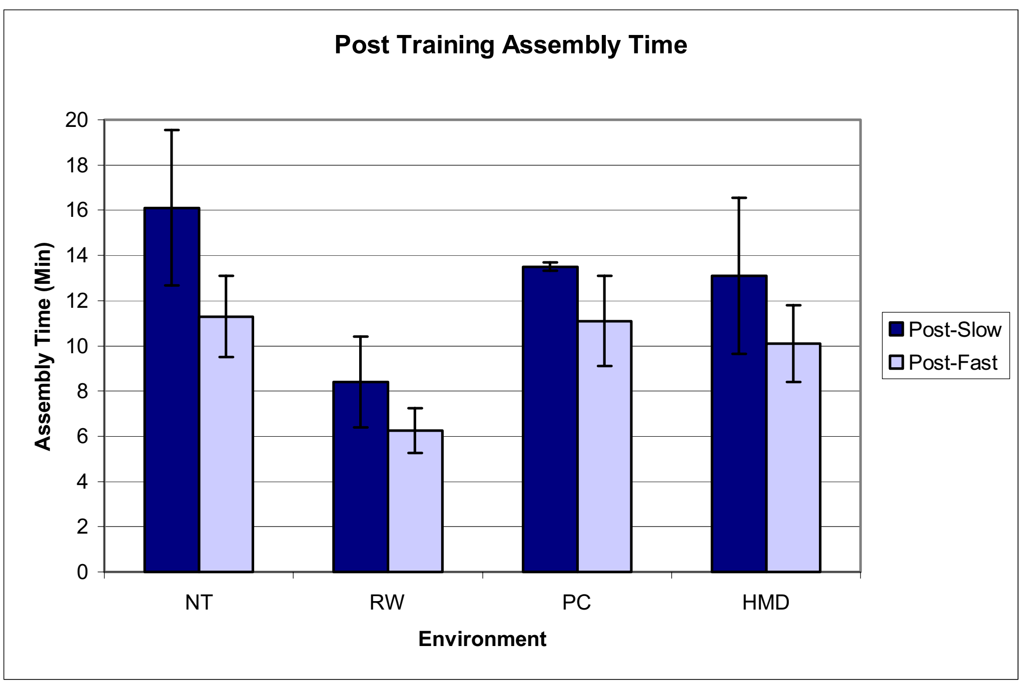

Figure 5. Mean improvement and standard deviations showing the amount of improvement between the pre- and post-training assembly times by Training Environment

There was also a significant main effect for Building Group $F(1, 40) = 20.97$, $p < .001$, partial $\eta^2 = .974$, $1\text{-}\beta = .857$ as Slow Builders improved significantly more than Fast Builders (see Figures 6 and 7). The interaction between Training Environment and Building Group was not significant ($p = .333$).

Perhaps the most interesting results can be found in the post-hoc analyses comparing Training Environment and Building Group shown in Table 3. For example, there is no significant difference between the improvement of build times for the Fast Builders in the RW environment and the Slow Builders in the PC and HMD environments which might suggest that VEs can be as effective as real-world training environments for some participants.

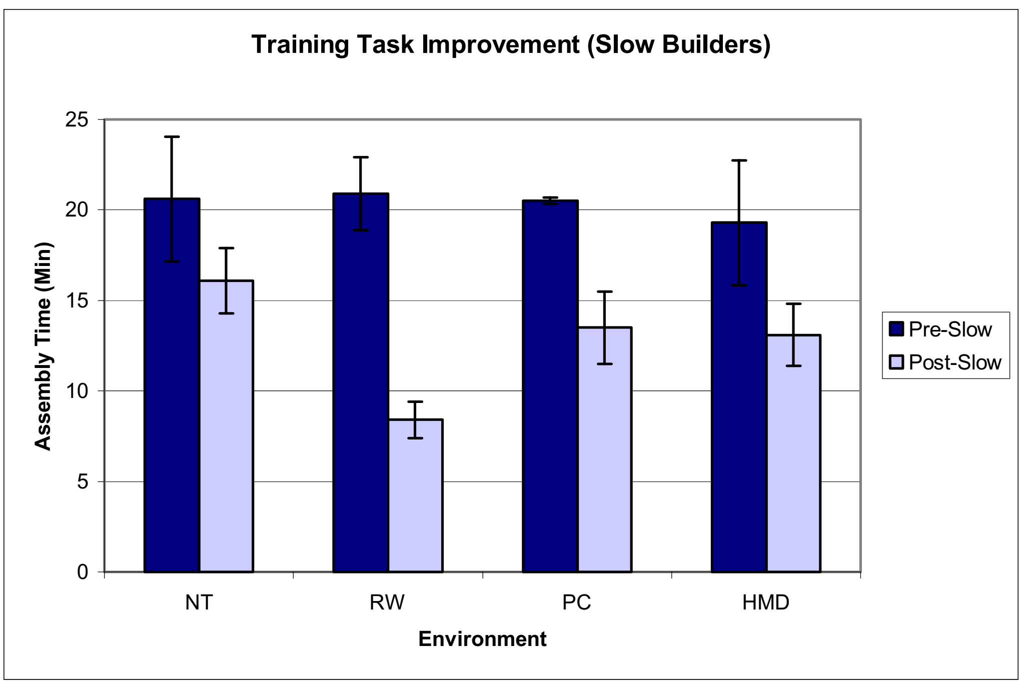

Figure 6. Mean Training Task Improvement scores and standard deviations for Slow Builders by Training Environment

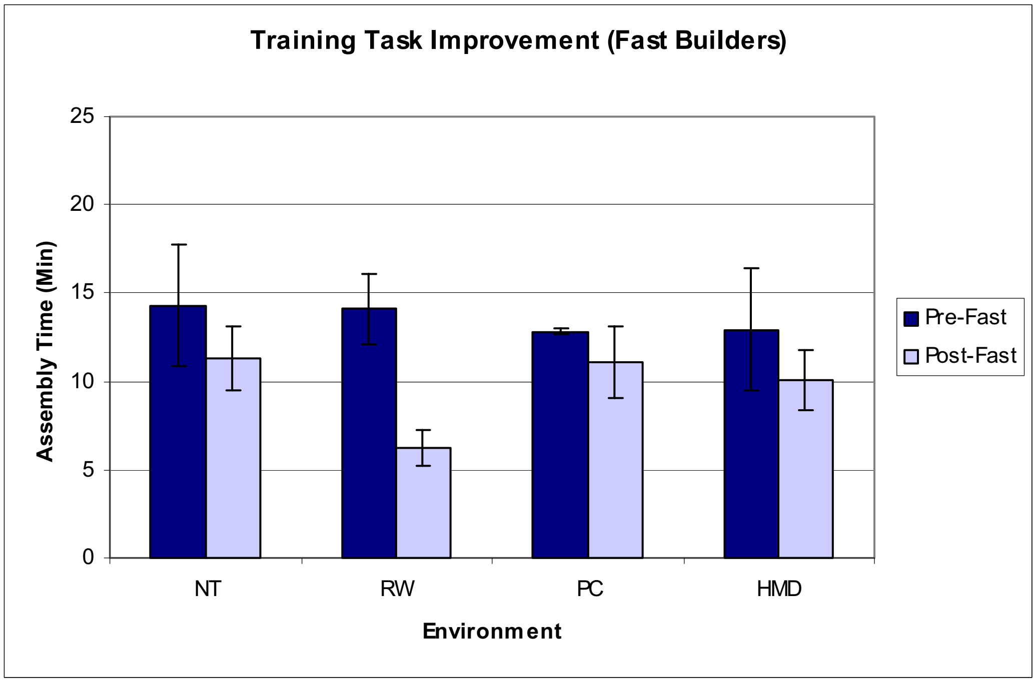

Figure 7. Mean Training Task Improvement scores and standard deviations for Fast Builders by Training Environment

		NT		RW		PC		HMD	
		Slow	Fast	Slow	Fast	Slow	Fast	Slow	Fast
NT	Slow		1.00	**.001**	.644	.764	.995	.442	.929
	Fast			**.001**	.205	.293	1.00	.107	1.00
RW	Slow				.125	.081	**.001**	.233	**.001**
	Fast					1.00	.225	1.00	.086
PC	Slow						.318	1.00	.086
	Fast							.120	1.00
HMD	Slow								**.041**
	Fast								

Table 3. P-values obtained from post-hoc analysis of Training Task Improvement scores by Training Time and Building Group

		M	SD
NT	Slow	4.83	5.11
	Fast	3.52	1.80
RW	Slow	12.53	2.40
	Fast	7.82	.92
PC	Slow	7.48	3.91
	Fast	3.60	1.56
HMD	Slow	8.35	3.60
	Fast	2.82	1.27

Table 4. Descriptive statistics for Training Task Improvement

Learning Task Improvement

Improvement on the Learning Test was calculated for participants by subtracting their Learning Test assembly time from their Pre-test assembly time. Individual improvement scores were subjected to a 2x4 between-subjects ANOVA.

Results showed no significant effect for Training Environment (p = .143). However, there was a significant main effect for Building Group F (1, 40) = 16.59, p < .001, partial η^2 = .293, 1-β = .973. There was also a significant interaction between the training environment and the training groups F (1, 40) = 2.95, p = .044, partial η^2 = .184, 1-β = .655.

Interestingly, Slow Builders assigned to the HMD training environment showed more improvement than all other participants regardless of their assigned environment or Builder Group. Post-hoc analysis (Tukey's HSD) are shown in Table 5. Analysis of mean assembly times also revealed the source of the interaction between Training Environments and Building Groups as the Slow Builders in the NT, PC and HMD groups improved significantly more than the Fast Builders in those same environments. However, the effect size of the interaction is rather small, making it somewhat irrelevant. It should be noted that the Fast Builders in the control group were the only group to perform the Learning Test slower than the Training Test as indicated by the negative improvement value shown in Figure 8.

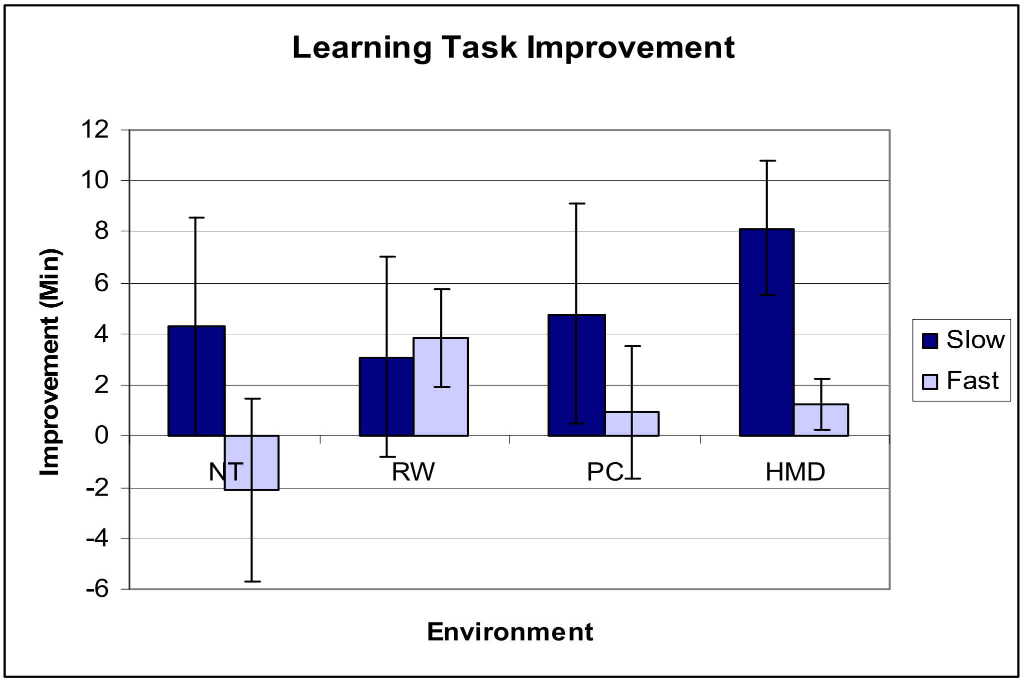

Figure 8. Mean Learning Task Improvement scores and standard deviations by Training Environment and Building Group

		NT		RW		PC		HMD	
		Slow	Fast	Slow	Fast	Slow	Fast	Slow	Fast
NT	Slow			.998	1.00	1.00	.619	.830	.728
	Fast			.132	**.054**	**.015**	.751	.001	.644
RW	Slow				1.00	.986	.934	.447	.972
	Fast					1.00	.765	.697	.855
PC	Slow						.457	.929	.569
	Fast							**.043**	1.00
HMD	Slow								.066
	Fast								

Table 5. P-values obtained from post-hoc analysis of Learning Task Improvement scores by Training Environment and Building Group

		M	SD
NT	Slow	4.29	4.30
	Fast	-2.07	3.60
RW	Slow	3.11	3.89
	Fast	3.85	1.94
PC	Slow	4.76	4.31
	Fast	.91	2.6
HMD	Slow	7.00	2.69
	Fast	1.24	1.05

Table 6. Descriptive statistics for Learning Task Improvement

Transfer of Training

Transfer of Training scores for each participant were calculated using Formula 2.3 and subjected to a 2x3 between-subjects ANOVA. Results showed a significant main effect for Training Environment F (2, 30) = 18.07, $p < .001$, partial $\eta^2 = .546$, $1\text{-}\beta = .960$ as the RW Environment achieved significantly higher rates of transfer than the virtual environments. Both virtual environments achieved moderate levels of transfer (i.e., greater than 100% improvement); however, the differences between them were insignificant (see Figure 9).

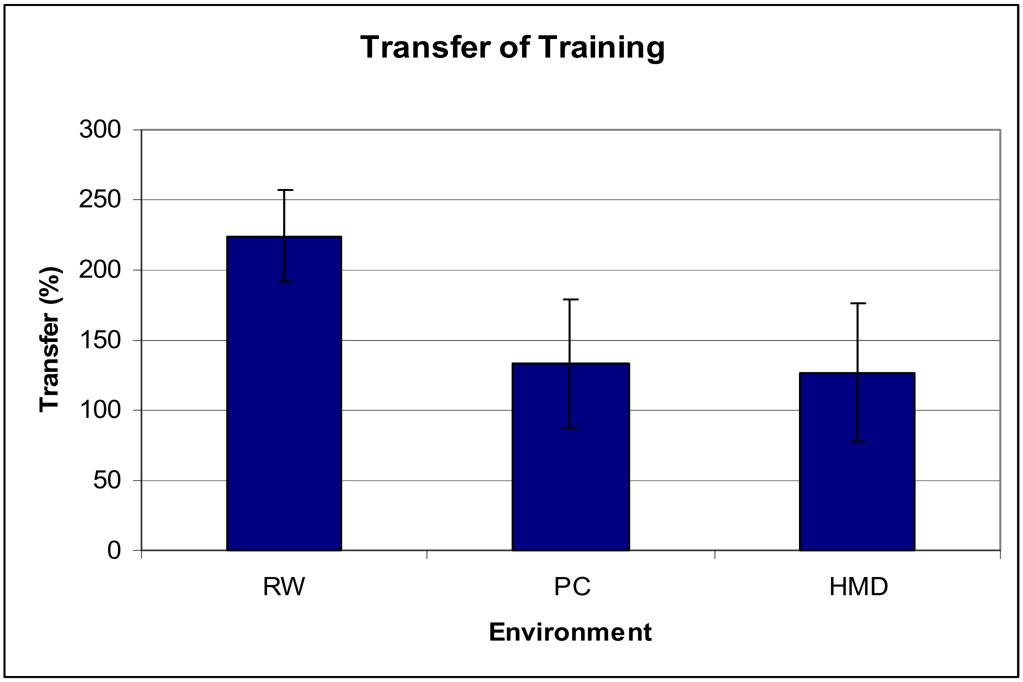

Figure 9. Mean Transfer of Training scores and standard deviations by Training Environment

There was no significant main effect for Building Group (p = .222) indicating that Fast and Slow Builders transferred the same amount of training per their respective Training Environment. However, graphical analysis of the means show that Slow Builders consistently achieved higher transfer scores than Fast Builders (see Figure 10). There was no significant interaction between Training Environment and Building Group. P-values comparing transfer across groups is shown in Table 7.

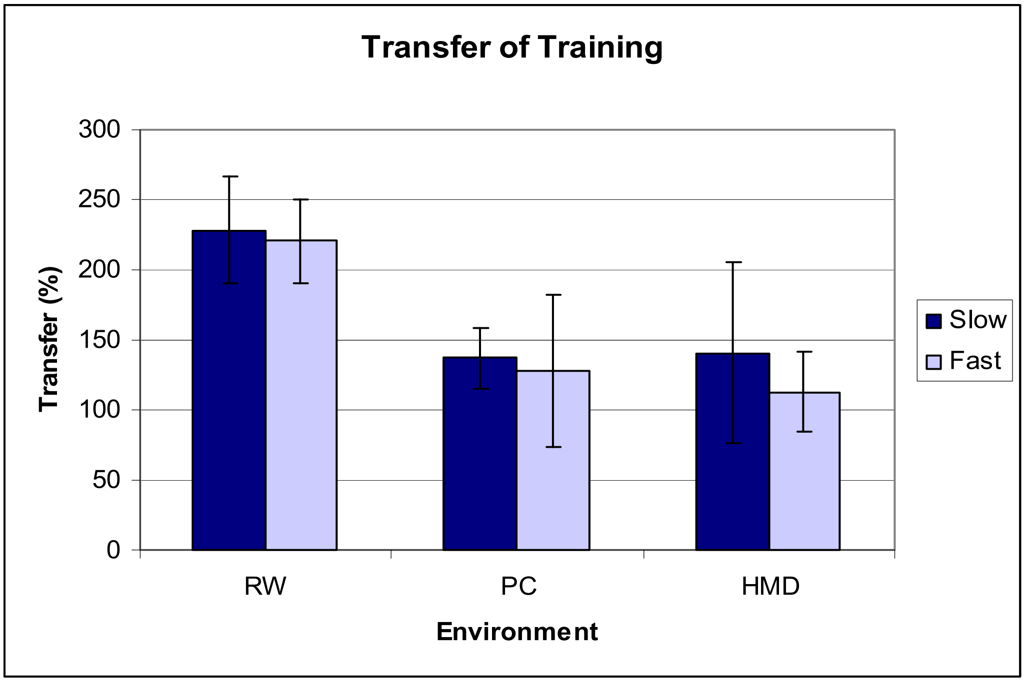

Figure 10. Mean Transfer of Training scores and standard deviations by Training Environment and Building Group

		RW		PC		HMD	
		Slow	Fast	Slow	Fast	Slow	Fast
RW	Slow		1.00	**.020**	**.008**	**.027**	**.001**
	Fast			**.045**	**.019**	**.063**	**.004**
PC	Slow				1.00	1.00	1.00
	Fast					1.00	1.00
HMD	Slow						1.00
	Fast						

Table 7. P-values obtained from post-hoc analysis of Transfer of Training by Training Environment and Building Group

		M	SD
RW	Slow	228.40	37.63
	Fast	220.19	29.47
PC	Slow	137.39	41.47
	Fast	127.79	53.96
HMD	Slow	140.69	64.26
	Fast	112.98	28.52

Table 8. Descriptive statistics for Transfer of Training

Transfer of Learning

Transfer of Learning scores for each participant were calculated using Formula 2.5. Testing for homogeneity of variance found significant variance by group interaction (*Levene's* (5, 30) = 4.562, $p = .001$). An inverse transformation was performed on the data prior to analysis to minimize potential of a Type I error (*Levene's* (5, 30) = 1.2602, $p = .307$). Transformed data was subjected to a 2x3 between-subjects ANOVA. Results showed no significant effect for Training Environment ($p < .105$) or Building Group ($p = .649$). The interaction was not significant ($p = .074$).

Interpretation of results from Transfer of Learning is difficult due to the amount of variance within the training environments and building groups. However, graphical analysis of the means shown in Figure 11 suggest that transfer of learning did occur, especially for Slow Builders in the virtual training groups.

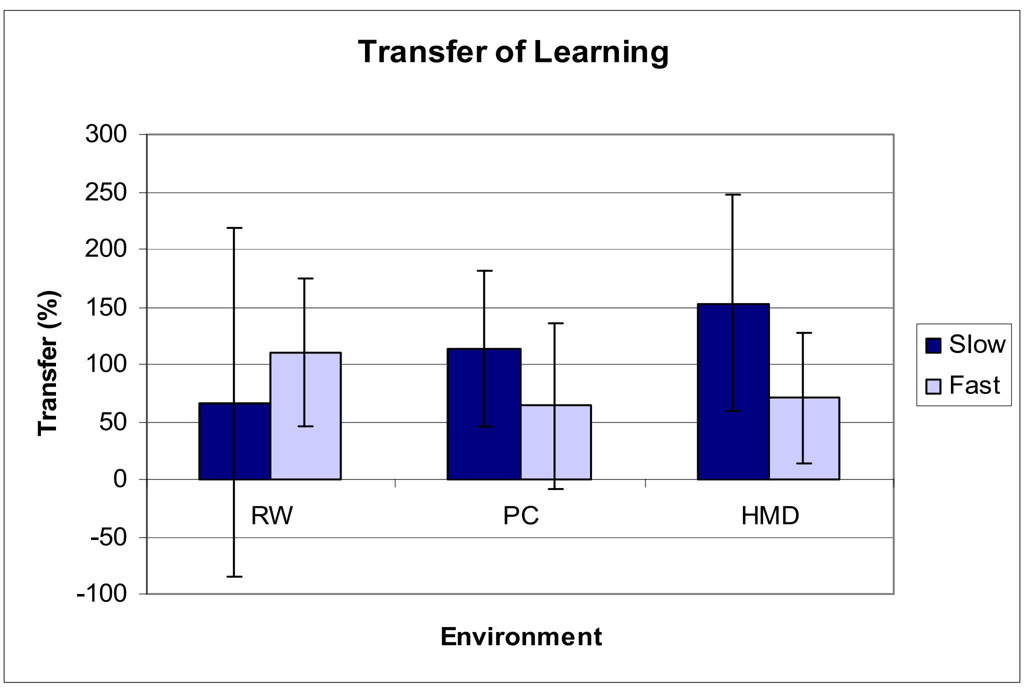

Figure 11. Mean (non-transformed) Transfer of Learning scores and standard deviations by Training Environment and Building Group

		M	SD
RW	Slow	-.008	.017
	Fast	-.025	.075
PC	Slow	.038	.073
	Fast	.020	.049
HMD	Slow	.057	.124
	Fast	.053	.104

Table 9. Descriptive statistics (transformed) for Transfer of Learning

Total Training Time

Total training time was calculated for each participant by summing the training times for all four training sessions ($\sum (T_1,T_2,T_3,T_4)$). Testing for homogeneity of variance found significant variance by group interaction (*Levene's* (5, 30) = 11.81, $p < .001$). A logarithmic transformation was performed on the data prior to analysis to minimize potential of a Type I error (*Levene's* (5, 30) = 1.364, $p = .266$). Transformed values were subjected to a 2x3 between-subjects ANOVA.

Results showed a significant main effect for Training Environment $F(2, 30) = 68.28$, $p < .001$, partial $\eta^2 = .820$, $1\text{-}\beta = .973$, as participants in the PC environment took longer that the other training environments. Post-hoc analysis (Tukey's HSD) showed that differences between all the experimental environments were significant (see Table 10).

A significant main effect was also found for Building Group $F(1, 30) = 6.625$, $p = .015$, partial $\eta^2 = .181$, $1\text{-}\beta = .703$. There was no significant interaction ($p = .237$). Participants in the RW training environment spent significantly less time training while the PC training environment required significantly more time than the other training groups (see Figure 13). P-values obtained from post-hoc analysis (Tukey's HSD) of Total Training Time of all the groups are shown in Table 10. Interestingly, the total training time for the Fast and Slow Builders in the HMD environment is significantly less than their counterparts in the PC environment.

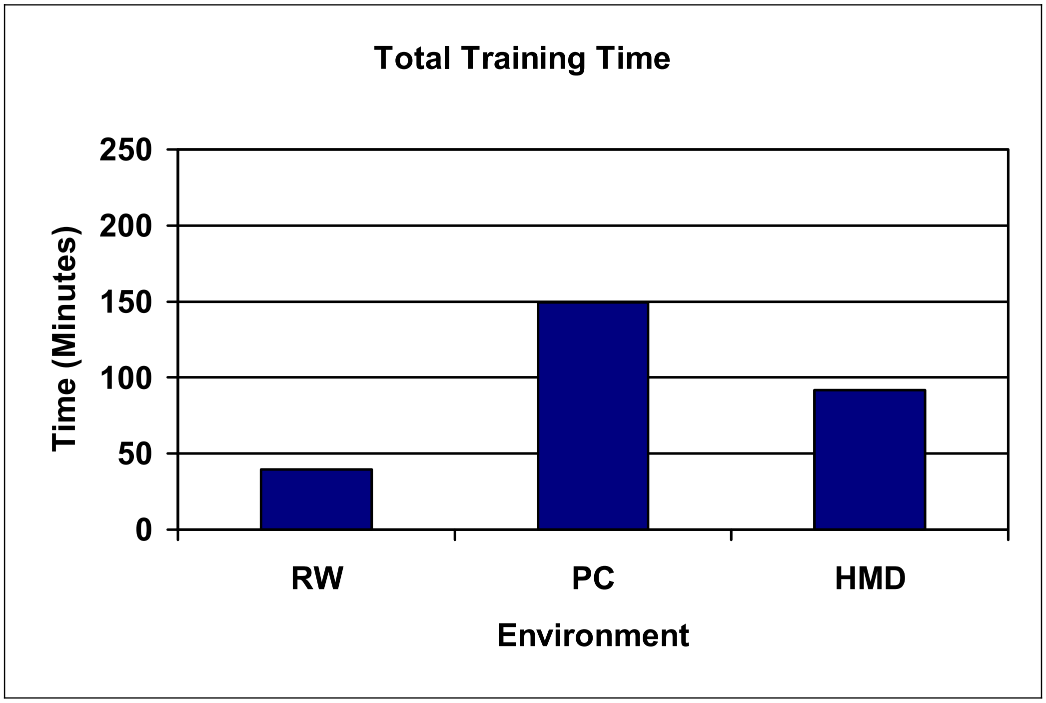

Figure 12. Total Training Time by Training Environment

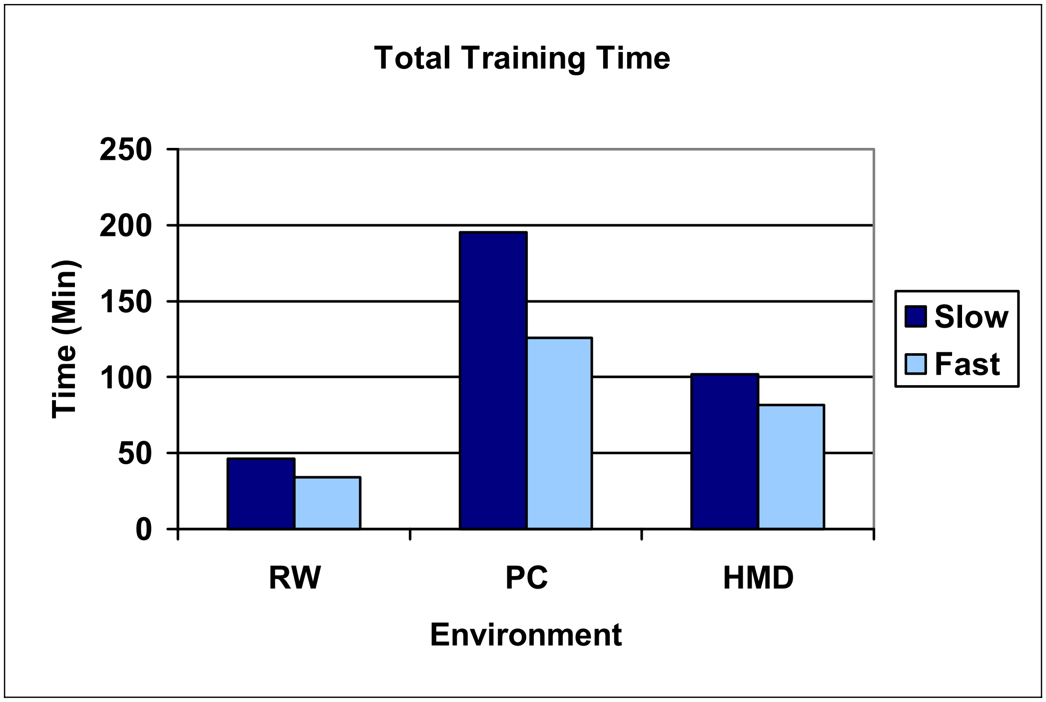

Figure 13. Total Training Time by Training Environment and Building Group

		RW		PC		HMD	
		Slow	Fast	Slow	Fast	Slow	Fast
RW	Slow		.069	**.001**	**.001**	**.001**	**.002**
	Fast			**.001**	**.001**	**.001**	**.001**
PC	Slow				.985	**.001**	.197
	Fast					.962	.535
HMD	Slow						.944
	Fast						

Table 10. P-values obtained from post-hoc analysis of transformed scores of Total Training Time by Training Environment and Building Group

		M	SD
RW	Slow	.023	.006
	Fast	.031	.007
PC	Slow	.007	.003
	Fast	.008	.003
HMD	Slow	.010	.003
	Fast	.013	.003

Table 11. Descriptive statistics (transformed) for Total Training Time

Training Time by Trial

To better understand the learning rate for each training environment and building group, mean training times were calculated for each trial and subjected to a 2x3x4 mixed-factors ANOVA with the four training trials analyzed as a within-subjects factor and Training Environment and Building Group analyzed as between-subjects factors. Mauchley's test for sphericity was significant indicating homogeneity of variance for one or more of the main effects. A logarithmic transformation was applied to the Total Training Times. After the transformation was applied Mauchly's Test of Sphericity was no longer significant ($p = .135$).

Results showed a significant main effect for Training Trial F (2, 28) = 121.00, $p < .001$, partial $\eta^2 = .928$, $1\text{-}\beta = .973$, and a significant interaction between Training Trial and Training Environment F (6, 58) = 4.967, $p < .001$, partial $\eta^2 = .339$, $1\text{-}\beta = .986$. The interaction between Training Trial and Building Group was not significant ($p = .651$). Participants in the RW training environment required significantly less training time than those in the virtual training environments while the PC training environment required significantly more time than the other training groups (see Figures 14 and 15).

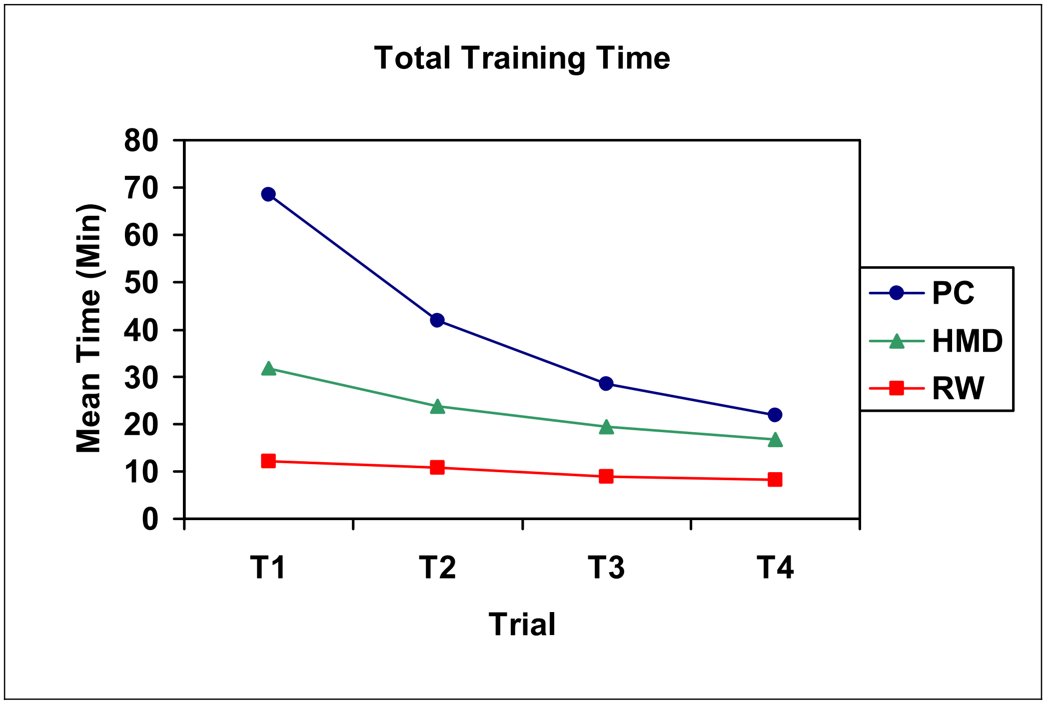

Figure 14. Mean (non-transformed) values for Total Training Time by Training Environment

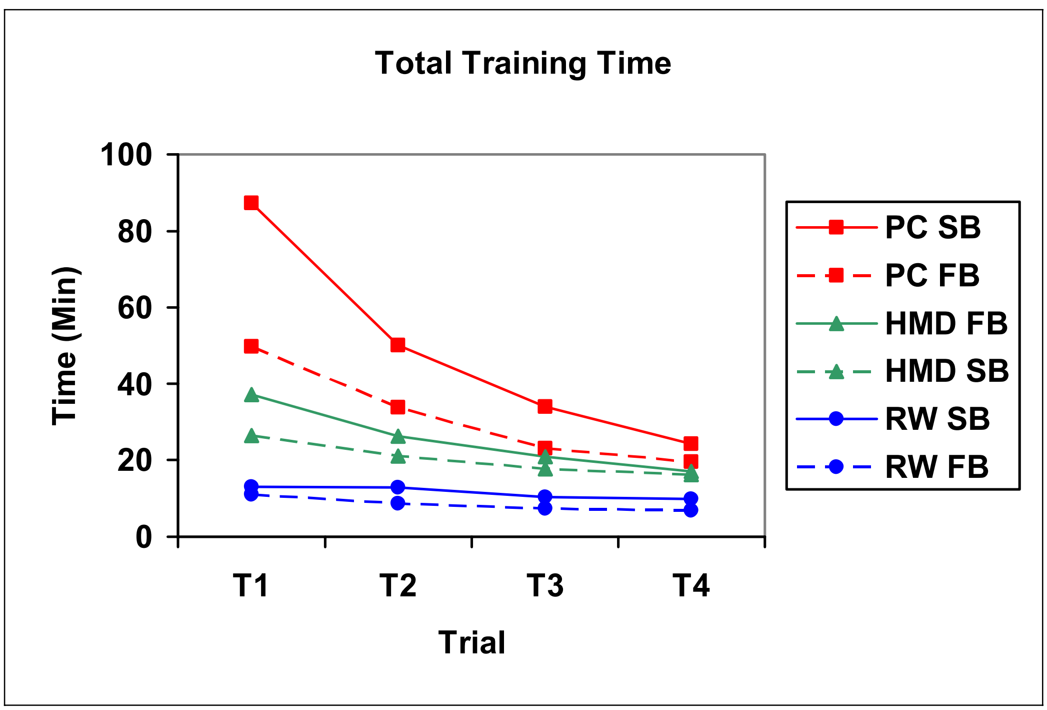

Figure 15. Mean (non-transformed) values of Total Training Time by Training Environment and Building Group

Training Efficiency

Training Efficiency was calculated for each participant using Formula 2.4. Testing for homogeneity of variance found significant variance by group interaction (*Levene's* (5, 30) = 6.55, $p < .001$). A logarithmic transformation was performed on the data prior to analysis to minimize potential of a Type I error (*Levene's* (5, 30) = 0.58, $p = .712$). Transformed values were subjected to 2x3 between-subjects ANOVA.

Results showed a significant main effect for Training Environment F (3, 30) = 44.83, $p <.001$, partial $\eta^2 = .782$, $1-\beta = .997$, as participants in the RW environment were significantly more efficient that participants assigned to the virtual training groups. There was no significant difference between the PC and HMD environments (see Figure 16).

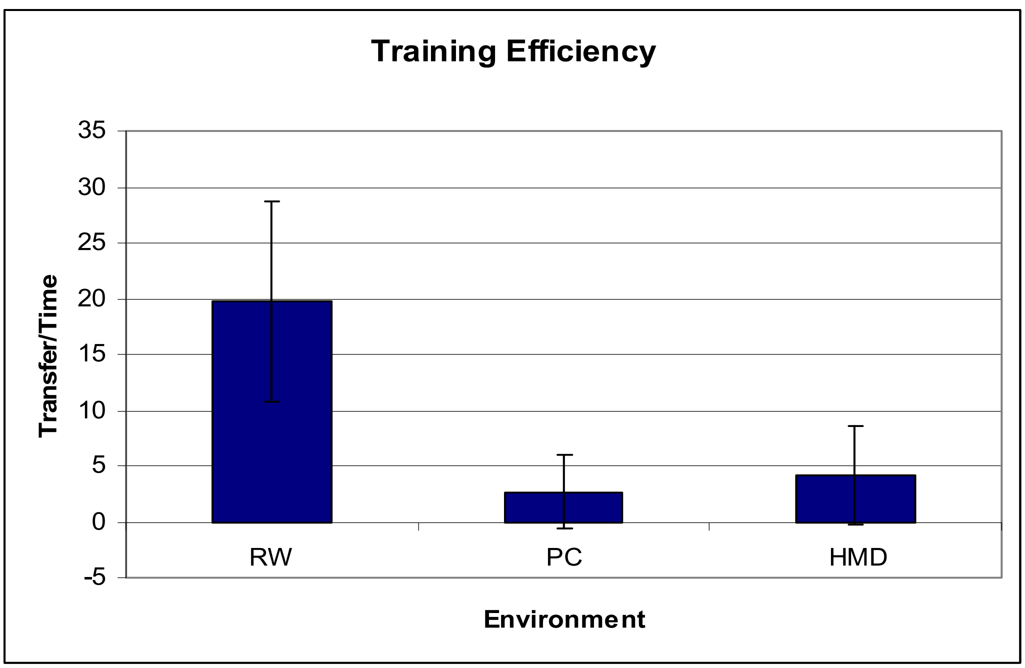

Figure 16. Mean (non-transformed) Training Efficiency scores and standard deviations by Training Environment

A significant main effect was also found for Building Group F (1, 30) = 23.663, p <.001, partial η^2 = .471, 1-β = .995. There was no significant interaction (p = .266). Not surprisingly the RW environment outperformed the other training environments. Interestingly the Slow Builders were far more efficient than the Fast Builders in all training environments (see Figure 17). P-values obtained from post-hoc analysis of efficiency calculations Training Environment and Building Group are shown in Table 12.

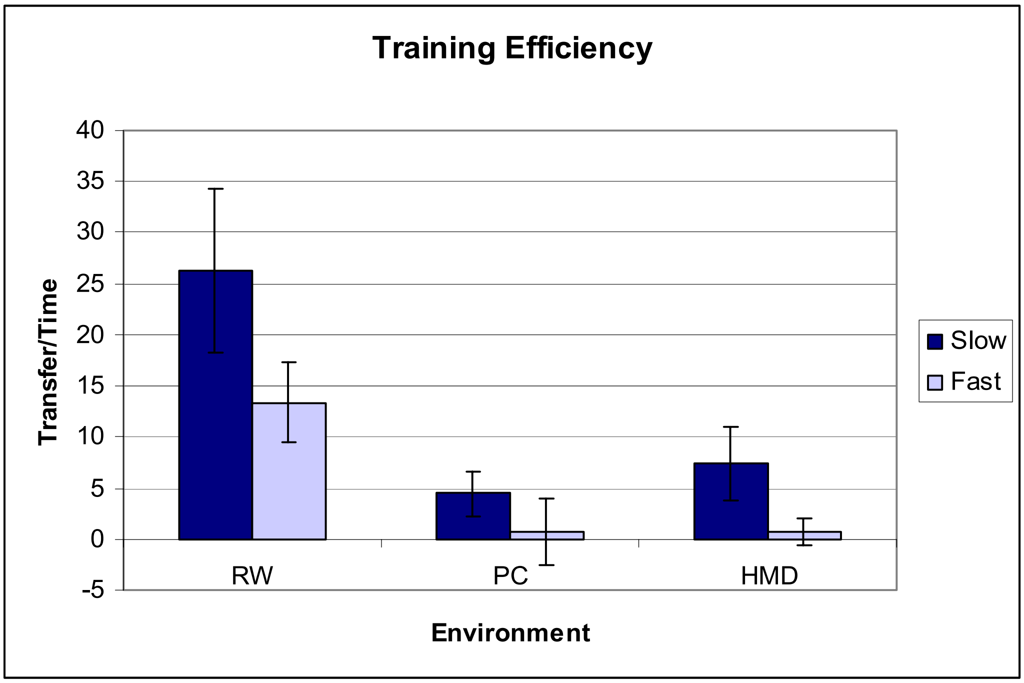

Figure 17. Mean (non-transformed) Training Efficiency scores and standard deviations by Training Environment and Building Group

		RW		PC		HMD	
		Slow	Fast	Slow	Fast	Slow	Fast
RW	Slow		**.028**	**.001**	**.001**	**.001**	**.001**
	Fast			**.001**	**.001**	**.020**	**.001**
PC	Slow				.064	.133	**.018**
	Fast					**.003**	.489
HMD	Slow						**.001**
	Fast						

Table 12. P-values obtained from post-hoc analysis of transformed scores of Training Efficiency by Training Environment and Building Group

		M	SD
RW	Slow	1.40	.15
	Fast	1.11	.11
PC	Slow	.62	.20
	Fast	.35	.28
HMD	Slow	.81	.29
	Fast	.23	.21

Table 13. Descriptive statistics (transformed) for Training Efficiency

Learning Efficiency

Learning Efficiency was calculated for each participant using Formula 2.4. Testing for homogeneity of variance found significant variance by group interaction (*Levene's* (5, 30) = 4.227, p = .005). A square root transformation was performed on the data prior to analysis to minimize potential of a Type I error (*Levene's* (5, 30) = 0.78, p = .577). Transformed data was subjected to 2x3 between-subjects ANOVA.

Results revealed a significant main effect for Training Environment F (2, 30) = 10.96, $p < .001$, partial $\eta^2 = .477$, $1-\beta = .982$ as once again the RW group was most efficient and there was no significant difference between the two virtual environments (see Figure 18).

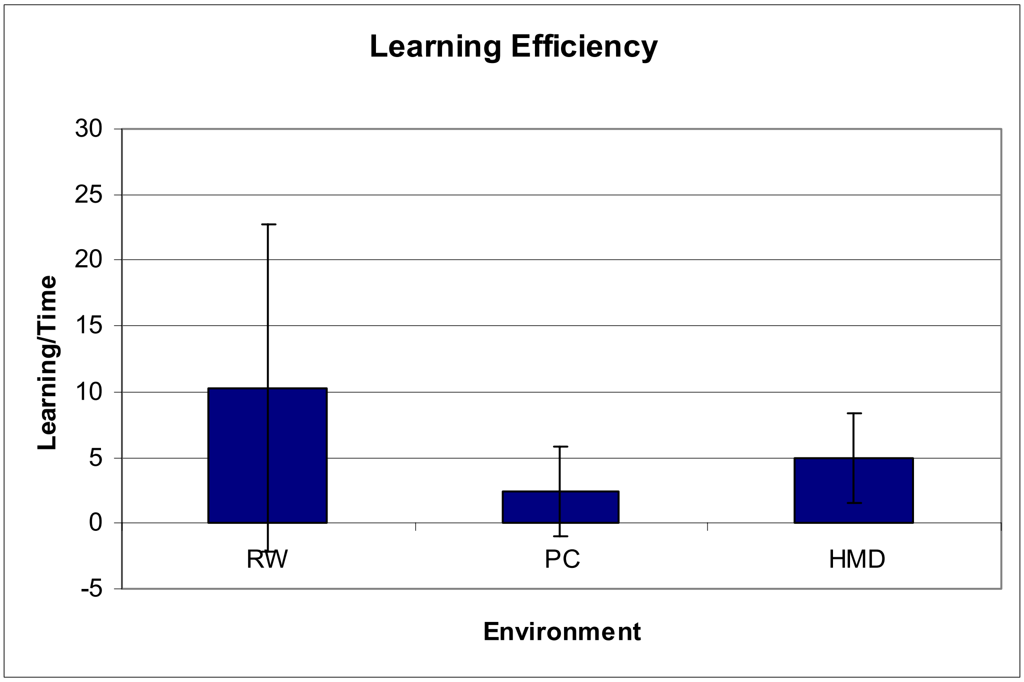

Figure 18. Mean (non-transformed) Learning Efficiency scores and standard deviations by Training Environment

There was also a significant main effect for Building Group $F(1, 30) = 8.97$, $p = .006$, partial $\eta^2 = .272$, $1\text{-}\beta = .820$ as Fast Builders were consistently more efficient than their counterparts. There was no significant interaction ($p = .501$). Pairwise comparisons revealed that the Fast Builders in the RW environment outperformed the other environments (see Figure 19). P-values from post-hoc analysis are shown in Table 14. It is important to note that the differences in learning efficiency between the Slow Builders in the RW and HMD environments were not significant which suggests that HMD training environments can be as efficient as real-world training environments.

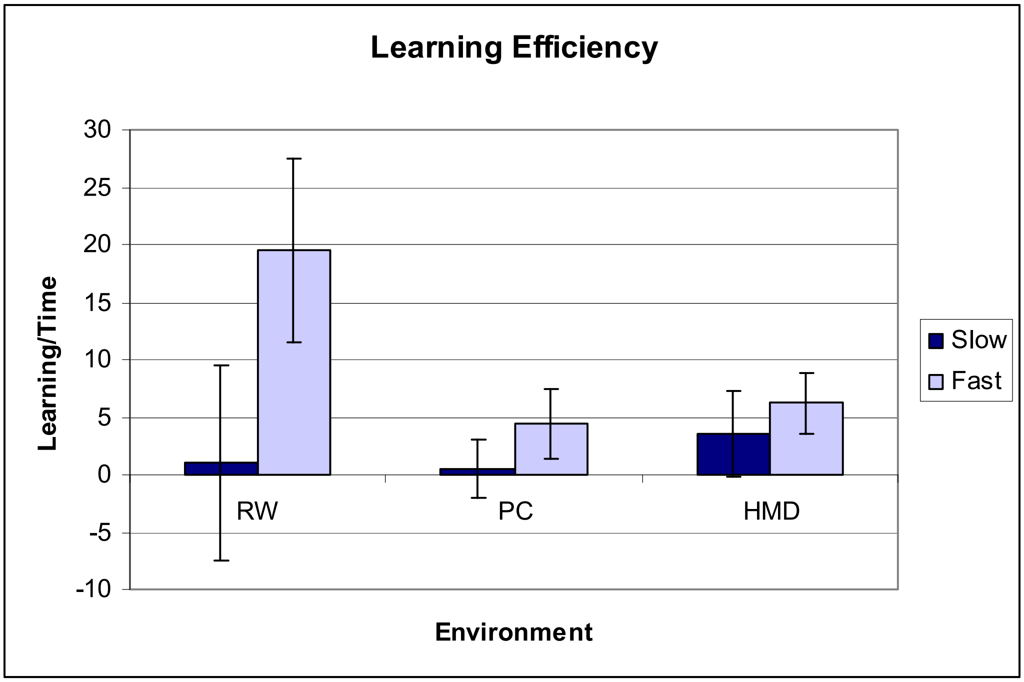

Figure 19. Mean (non-transformed) Learning Efficiency scores and standard deviations by Training Environment and Building Group

		RW		PC		HMD	
		Slow	Fast	Slow	Fast	Slow	Fast
RW	Slow		**.017**	**.058**	.211	.080	.602
	Fast			**.001**	**.001**	**.001**	**.001**
PC	Slow				.319	.640	.089
	Fast					.512	.363
HMD	Slow						.124
	Fast						

Table 14. P-values obtained from post-hoc analysis of transformed Learning Efficiency scores between training Environment and Building Group

		M	SD
RW	Slow	2.77	.94
	Fast	4.31	1.06
PC	Slow	1.38	.73
	Fast	1.99	.71
HMD	Slow	1.66	.99
	Fast	2.44	.52

Table 15. Descriptive statistics (transformed) for Learning Efficiency

Individual Differences

WPT and MRT: T-tests revealed significant differences between participants classified as Fast Builders to those classified as Slow Builders with relation to their scores on the WPT ($t = 37.95$, $p < .001$) and Mental Rotations Tests ($t = 20.75$, $p < .001$. Fast Builders, on average scored higher on both tests (see Figure 20). Correlations between building group and scores on each test were also significant (WPT ($r = .453$, $p < .001$) and the MRT ($r = .431$, $p < .001$)).

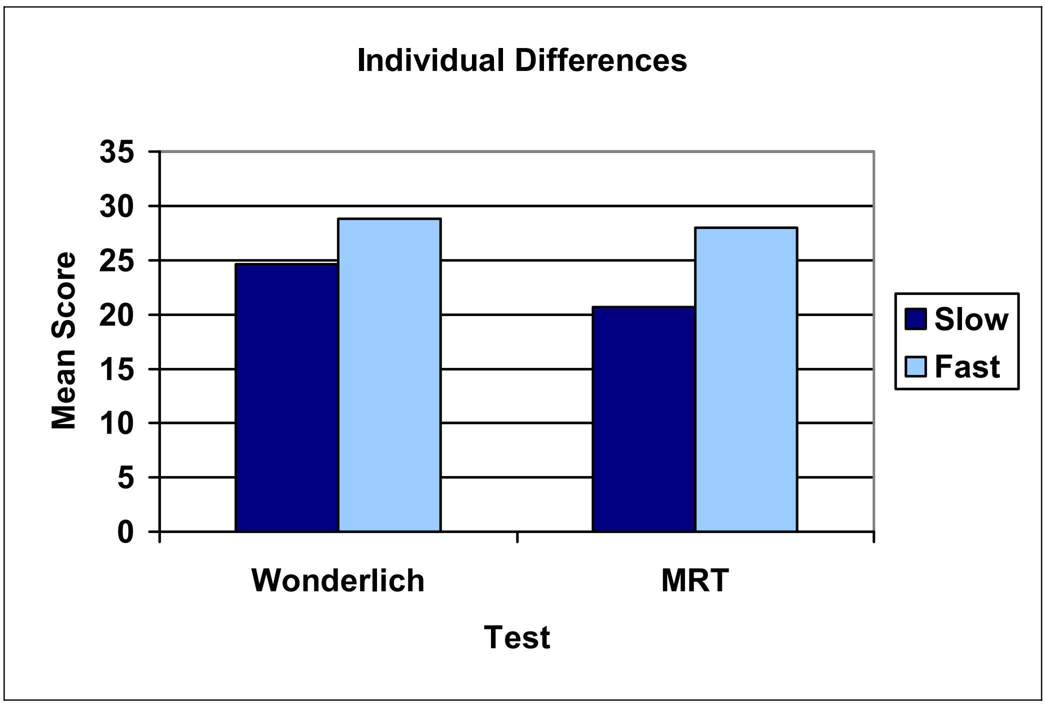

Figure 20. Mean scores obtained on the WPT and MRT tests by Building Group

Scores obtained from the WPT and MRT were correlated to participant's Pre-test, Post-test, Learning Test assembly times, Total Training Time, Training Efficiency and Learning Efficiency. Results of Pearson's r correlation to Pre-test assembly times showed a significant negative relationship between the WPT ($r = -.425$, $p < .001$) and the MRT ($r = -.499$, $p < .001$), indicating the higher scores on both tests correlated to faster assembly times. Not surprisingly, similar relationships were found for the results of the Post-test assembly times: WPT ($r = -.303$, $p = .018$) and the MRT ($r = -.408$, $p = .002$). Significant negative relationships were also found for the Learning Test assembly times. WPT ($r = -.384$, $p = .003$) and the MRT ($r = -.489$, $p < .001$).

There was no significant relationship between Total Training Time and WPT scores; however, the relationship with the MRT scores approached significance ($r = -.272$, $p = .054$), thereby suggesting that higher MRT scores resulted in faster training times. There was no significant relationship between Training Efficiency and the WPT or MRT ($p = .152$ and $.421$, respectively). However, there were significant positive relationships with Learning Efficiency and the WPT ($r = .279$, $p = .049$) and the MRT ($r = .428$, $p = .005$), which suggests that higher MRT scores result in more efficient learning of the assembly task.

CUSE: Scores obtained from the CUSE were also correlated to the dependant variables given above. Results revealed a significant negative relationship with Total Training Time ($r = -.405$, $p = .007$), suggesting that higher CUSE scores resulted in lower Total Training Times. Results also revealed positive relationships with Training efficiency ($r = .542$, $p < .001$) and Learning Efficiency ($r = .325$, $p = .027$), which suggests that higher CUSE scores correlated to higher efficiency for both training and learning tasks.

It is most interesting to note that the correlations increase when the scores from the virtual training groups are isolated. Correlations to Total Training Time increased to .581, ($p < .001$). Likewise, Training efficiency increased to .681 ($p < .001$), and Learning

Efficiency increased slightly to .344 (p = .040). These differences in correlations further support the suggestion that CUSE scores may predict learning ability in VEs.

Gender: T-tests revealed a significant effect of Gender on Transfer of Training scores (t = 15.428, p < .001) as females, on average, achieved higher levels of transfer; however, there was no affect for Transfer of Learning (p = .141). There was a significant effect for Gender on Total Training Time (t = 9.11, p = .005) as Females, on average, had faster assembly times. Significant effects were also found for Transfer of Training Efficiency (t = 8.12, p = .008) and Transfer of Learning Efficiency (t = 5.396, p = .028) as Females, on average, obtained higher efficiency scores.

A significant effect for Gender was not found for the WPT (p = .338); however, significant effects were found for the MRT (t = 7.45, p = .009) and the CUSE (t = 9.89, p = .003) as Males, on average, achieved higher scores on both tests.

CHAPTER 4

DISCUSSION

Results of the study show that: 1) VEs can be effective simulators for training real-world assembly tasks although they are not as effective as real-world training 2) VEs are less efficient than real-world training; however, full-immersive environments require less training time than a PC training environment 3) individual differences such as general intelligence, spatial aptitude, computer-user self-efficacy, and gender affect one's ability to learn in VEs.

At first glance the performance of the virtual training groups compared to the performance of the RW training group may lead one to interpret results somewhat negatively. However, while it is readily apparent that the RW training environment outperformed the virtual training environments on almost every dependent measure, it is important to keep in mind that the participants in the VEs did improve, on average reducing their assembly time by half.

Post-training Improvement

Analysis of post-training assembly times for both assembly tasks show improvement for both virtual training environments. In fact, training task improvement times of Slow Builders in the VEs were shown to be equivalent to those of Fast Builders in the RW environment. This result suggests that VEs can be as effective as the RW environment but consideration needs to be given to the task to be trained along with the existing skill and expertise of the trainee (Darken & Banker, 1998). Additional evidence of this can be found in the differences between Fast and Slow Builders on Transfer of Learning scores. When faced with a similar but distinct assembly task, Slow Builders trained in the HMD environment transfer skills and knowledge learned more effectively than builders in other training environments

Despite the lack of statistical significance, graphical analyses of the mean improvement times of Slow Builders on the learning task provide evidence that the virtual environments may provide an advantage when transferring skills to a novel task. It is worth noting that the Slow Builders in the HMD group, on average, demonstrated approximately 50% more improvement over their counterparts in the PC environment and approximately 70% more than the RW environment. Together, these results show that the skills and knowledge learned during virtual training are useful when performing the same assembly task in the real world.

Positive transfer was found for both the training and learning assembly tasks with both groups achieving greater than 100% improvement. The fact that differences between the Building Groups in the two VEs were not significant suggests that neither environment provides a significant advantage when it comes to transfer of training. The lack of significant differences between the two virtual training groups are similar those reported by Waller et al., (1998) who found no significant differences between a PC-based VE and an HMD-based VE that received the same training time to navigate a virtual maze.

Total Training Time

Results obtained from the measure of Total Training Time revealed that the virtual environments required more significantly more training time than real-world training and the PC environment required the most training time. This finding is also similar to results found by Waller et al., (1988) who found virtual training required longer training sessions, especially in the first few trials.

One potential reason for the differences in Total Training Time may lie in the lower interface fidelity of the PC environment. As mentioned previously, the PC environment required use of a three-button mouse, which may have seemed awkward to a standard mouse user. In addition, the PC environment required the use of a keyboard to activate several function keys necessary to navigate the environment and manipulate parts, where the HMD environment required the participant to learn eight function keys (inputted using the pinch gloves), trainees in the PC environment were required to learn 13 function keys most of which required coordinated movements of the mouse and keyboard. The additional function keys are primarily needed to control navigation in the PC environment and are not required by the HMD environment due primarily to motion tracking capabilities. Thus, it would seem that the pinch gloves provide a more intuitive input device for this particular task.

The additional requirement of having to learn the mouse controls and function keys may have interfered with the trainee's ability to concentrate on the learning the assembly task. Evidence of this can be found in the learning curves for each training environment and observations made by the experimenter during data collection. The learning curves, especially those of the virtual environments, begin significantly higher than the RW and NT training environments. The slopes of the learning curves show dramatic improvement in the first two training sessions which indicate two things: 1) learning to operate the VE required the development of additional skills and strategies to complete the assembly task, 2) most of the improvement in the first two training trials is associated with learning to manipulate the environment rather than learning the assembly task. It is interesting to note that improvement in the post training tasks show that the skills acquired were useful for performing the real world task. In addition, participants in the VE's developed new skills that were specific to successfully navigating and manipulating the virtual training environment. The experimenter observed motor movements that increased in complexity as the participants practiced. Participants were also observed planning multiple moves in order to more efficiently complete a particular procedure. The execution of simultaneous inputs and the planning of multiple moves prior to their execution most likely accounts for the improvements time on task recorded in the later trials.

Skill Acquisition

During data collection transition through the levels of skill acquisition described by Anderson (1982) and Fitts and Posner (1967) were observed as the participants practiced in their respective environments. For example, in the early stages of training participants in the HMD environment typically made distinct head movements followed by slow and deliberate hand movements and finger gestures. As training progressed and the participant adapted to their training environment, head and hand movements were observed occurring concurrently along with finger gestures. In fact, often during the later training sessions participants needed to be cautioned against making concurrent finger gestures with their right and left hands to prevent the software from canceling one or both of the inputs.

Likewise participants in the PC-based virtual environment were observed making distinct movements along a single axis followed by another movement along a second axis and so on, as they navigated to a desired viewpoint. However, as training progressed participants began making movements along multiple axes. In addition, it was observed that during later training sessions participants in the virtual environments began selecting all of the parts that they needed for a particular step prior to attaching them to the assembly. This in contrast to their behavior observed in the early training session where they selected each part separately and attached it to the assembly prior to selecting and positioning the next part.

Applying the theories of skill acquisition discussed previously (Anderson, 1982; Fitts and Posner, 1967), these observations suggest two things. First, participants had adapted to their respective environment to a level that allowed them to develop specialized skills for their respective environment, which resulted in lower trial times. Second, participants had learned the procedural task to the degree that they began planning multiple moves necessary to accomplish each step. The adoption of new skills and the preplanning of movements are indicative of the Fitts' (1967) associative stage and the acquisition of Anderson's Procedural Knowledge (1982). Thus it would seem appropriate that future studies should closely examine the specific physical and cognitive skills that are learned as a user adapts to a particular virtual environment. The observations from this study suggest that the quantity of parallel cognitive and motor processes increase as skill increases. Thus after an initial adaptation to the environment, movements and thought processes require less conscious control and the participants began to concentrate on learning the assembly task rather than learning how to manipulate their particular environment.

Simulator Fidelity

It is interesting to note that there seems to be a ceiling effect for how fast participants can assemble parts in the virtual environment. There are several factors that contribute to the ceiling effect including the processing speed of the computer, refresh rate of the display system, and the fact that the pinch gloves only allow for one-handed manipulation of the virtual objects. For example in the HMD environment, the responsiveness of the display device lags behind the physical movements of the trainee. While this delay is on the order of hundredths of a second, it is enough to perturb the motor movements of the trainee. These perturbations increase the number secondary or "tuning" motor movements required to reach for and acquire a virtual part, which results in increased assembly times. The lack of haptic feedback likely exacerbates this problem. This observation is consistent with results reported by Ware and Balakrishnan (1994) and Werkhoven and Goren (1998).

Another explanation for the increased training time is that the PC environment may have also lacked the level of environmental fidelity that the participants in the HMD environment experienced. Environmental fidelity was primarily affected by the lack of stereoscopic vision, which a typical desktop monitor does not provide. Learning to manipulate objects in a virtual environment without stereovision proved to be a challenging task for participants assigned to the PC environment. Often times the participants would align a part with the assembly expecting the part to snap into place only to discover that the part was aligned in one dimension but not another. This forced participants to spend additional time attaching a part to the assembly. The experimenter observed that by about the 2nd or 3rd trial most of the participants had adopted a strategy of aligning the parts in one dimension then changing their perspective to align a part in another perspective. Some of the more astute participants adopted the strategy of using the cardinal views (i.e., front view, top view, and side views) to align their parts. Once the parts were aligned with the assembly, participants were still faced with the challenge of rotating the part on its axes to the proper orientation required to fit onto the assembly; however, this proved to be more challenging than navigating the environment. Subsequently, participants in the PC environment relied more upon the snap-to function than the HMD group. This apparently did not affect their transfer of training, as results between the two virtual environments are similar.

It could be argued that the PC environment was not optimized to take advantage of the affordances and constraints of the peripheral devices used. For example, both environments may have benefited from a virtual parts menu that would allow participants to drag parts from the menu into the virtual environments as opposed to having the parts arranged in the virtual environment. Such a menu would perhaps minimize visual search time and navigation required to acquire and assemble the parts. Perhaps a three-dimensional joystick would have improved the effectiveness and efficiency of the participants in the PC environment. A three-dimensional joystick might minimize the number of function keys that the participants needed to memorize in order to navigate and manipulate objects in the environment thus improving navigation and object manipulation.

However, this study was specifically interested in determining how closely the visual and physical cues needed to be in order to train a complex manual assembly task. The results thus far seem to suggest that the physical attributes need not be an absolute replica given the lack of significant differences between the virtual environments. However, results obtained from measures of training effectiveness suggest there is an advantage to training in a full-immersive environment. Though not significant, the results show that Slow Builders in the HMD environment were more efficient than other participants assigned to a virtual environment.

Perhaps the most interesting results are those obtained from the measures of individual differences. As one would expect, general intelligence, as measured by the WPT, clearly plays a role in the transfer of training regardless of the type of training device used. The results obtained from the MRT show moderate but significant negative correlations between spatial aptitude and post-training times for both assembly tasks. That is, participants with higher scores on the MRT assembled the Lego™ models more quickly. This finding is especially interesting given Waller et al. (1998) failed to find a significant correlation using an alternate measure of spatial aptitude. Perhaps the reason for differing results lie in the tasks that were trained, since Waller et al. (1998) were evaluating a wayfinding task whereas this study evaluated an assembly task. Alternatively, the differences may lie in the intricacies of the two measures. Regardless, the results obtained from the MRT combined with the performance differences between fast and slow builders suggest that the MRT is a good predictor of user transfer of training from virtual training environments. Likewise, CUSE scores obtained from participants assigned to the virtual training environments provide a good predictor for Total Training Time, Training Efficiency and Learning Efficiency.

CHAPTER 5

CONCLUSION

The results found in this study suggest that virtual training is not appropriate for all training tasks. Rather, there seems to be a distinct threshold for the considerations of trainee safety, task complexity, and simulator costs must be weighed. It would seem that virtual training should be reserved for high-risk training environments (i.e., navigation of burning buildings) that are too hazardous or safety critical tasks (i.e., disassembly or maintenance of a nuclear device) that may be too expensive or too dangerous to duplicate in the real world.

Regardless of the technology employed, the best training device is one that that creates the highest level of subsequent performance in the operational environment with the least amount of expense and time. Clearly the results of this study show that virtual training environments fail to match the effectiveness or efficiency of a real-world training environment. Nonetheless, virtual training environments offer an effective training option for training tasks that may be too dangerous, costly or complex to duplicate in the real world.

While this study focused on determining the level of fidelity necessary to train a real-world assembly task, virtual training environments need not duplicate the real-world environment. Indeed, research has shown that mimicking the real world may not be ideal for all training scenarios. Schneider (1985) argues that the real world does not always present information in way that is optimal for learning. Virtual reality simulators provide the ability to alter information within the training scenario in ways that are not available in real-world scenarios. For example, controlling the transparency of walls in an office building or augmenting navigation with a virtual map or compass. Likewise, learning does not always occur optimally even when all of the information is present and available to the trainee (Carroll and Carrithers, 1984; Carroll, 1997). VE's have the potential to allow instructors to exercise a greater level of control over the training environment by either adding or subtracting information in a manner that optimizes information processing for the individual trainee within a given training scenario.

It would seem that the true advantage of virtual training is not merely in its ability to simulate virtual environments but rather in its potential to augment information provided in the training environment. Thus, psychologists, working along side computer scientists, move beyond merely simulating a training environment, and explore various methods of augmenting typical training curriculums with VE's that provide information in an efficient manner that is relevant and meaningful to the trainee.

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APPENDICES

APPENDIX A

Demographic Questionnaire

Name: ____

E-mail: ____ Phone: __________________

Age: ________

Major: ______________________ Minor: _________________________

Have you ever experienced motion sickness while:

Traveling by Car	☐ Always	☐ Often	☐ Rarely	☐ Never
Traveling by Boat	☐ Always	☐ Often	☐ Rarely	☐ Never
Traveling by Airplane	☐ Always	☐ Often	☐ Rarely	☐ Never
Riding an amusement park ride	☐ Always	☐ Often	☐ Rarely	☐ Never
Watching a Movie	☐ Always	☐ Often	☐ Rarely	☐ Never

Do you build with LEGOs now or did you as a child?
☐ Often ☐ Sometimes ☐ Never

Do you build with LEGO Technique now or did you as a child?
☐ Often ☐ Sometimes ☐ Never

How many hours are you taking this semester? _______

What days are you on Campus?
☐ Monday ☐ Tuesday ☐ Wednesday ☐ Thursday ☐ Friday

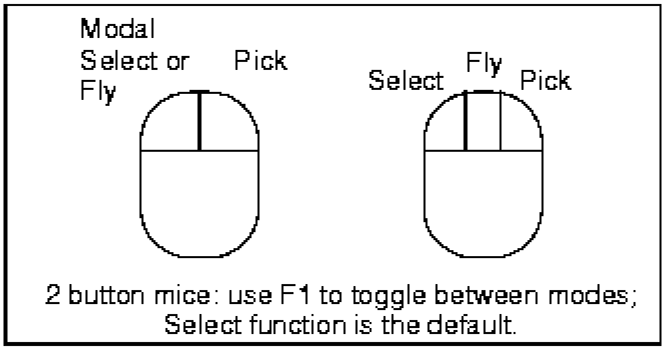
If chosen to participate in one of the training groups, will your schedule allow you participate on a daily basis for a full week (5 days Monday-Friday)?
☐ Yes ☐ No

APPENDIX B

Control Instructions for PC Training Environment

Navigation and Selection with the 2D Mouse

Allocation of Functions to 2 and 3 Button Mice



Selecting and Moving Assemblies
You select one or more assemblies by using the following mouse controls:

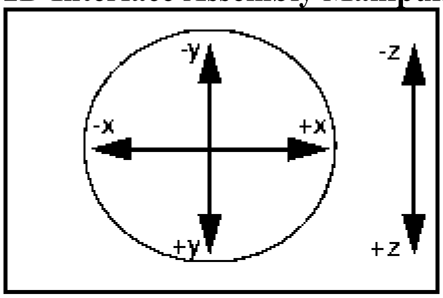
Mouse Button	Description
Left	To **select** an assembly, move the cursor over the desired assembly and press the left mouse button. Select again to deselect an assembly.
Ctrl+Left	To **select more than one assembly**, press and hold the Ctrl key while using the left mouse button to make your selections.
Alt+Left	To **fly to a selected assembly**.

You can move selected assemblies by using the following controls:

Mouse Button	Description
Right	Pressing the right button **after you have selected an assembly** causes the assembly to be Picked and allows you **to move the assembly** (see notes below).
Shift+Right	Using the Shift key and right mouse button together **after you have selected an assembly** causes the assembly to be Picked and allows you **to rotate the assembly** (see notes below).

Releasing the Right mouse button causes the selected assembly to be dropped.
When moving or rotating assemblies, the screen is divided into two invisible regions. By depressing and moving your mouse within the central region you can change the X or Y position or orientation of the assembly. When you depress the mouse outside the region you move or rotate relative to the Z axis.

2D Interface Assembly Manipulation Regions



Navigation Controls
The mouse buttons that you use to control flight are different for 2 and 3 button mice.

2 Button Mouse	3 Button Mouse	Cursor Movement	Description
Left	Middle	Up Down Left Right	Fly forward. Fly backward. Rotate left. Rotate right.
Left+Right	Middle+Right	Up Down Left Right	Move up. Move down. Move to the left. Move to the right.
Shift+Left	Shift+Middle	Up Down Left Right	Rotate view down. Rotate view up. Rotate view left. Rotate view right.
Ctrl+Left	Ctrl+Middle	Up, Down, Left, Right	Orbital movement (see notes below).

You can combine the Ctrl key with the left (or middle) mouse button to define an orbital movement about a point. By default the point is directly in front of you and 1m away, or will be the selected point on the surface of an assembly.

Keyboard Navigation Controls

You can use the following keys to define high level navigation controls:

Buttons/Keys	Description
Ctrl+a	Use this key sequence to **view all visible assemblies**.
Ctrl+Alt	Press the Ctrl and Alt keys simultaneously to **fly to assemblies that you have already selected**. **You must release the Alt key before the Ctrl key.**