Behavioral, Physiological, and Psychological Effects of Virtual Reality Practice in Immersive and Non-Immersive Environments.

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ABSTRACT

Virtual reality (VR) is one of the most rapidly advancing technologies that exists today. Although the current body of literature spans several disciplines and populations, inconsistences in defining "virtual reality" have complicated the interpretation and application of results. Some studies define VR as fully immersive environments delivered through head-mounted displays, while others use the term to describe non-immersive environments presented on a projected flat screen or a television or computer monitor. This literature review provides a working definition of VR followed by an examination of research on VR for motor skill learning.

The present dissertation investigated the effects of VR immersion on motor behavioral, physiological, and psychological outcomes by having participants complete the same stationary cycling task in both non-immersive and immersive VR environments. Study One evaluated participants across a single day of practice in each condition (two days total), providing foundational insights into how immersion influences various performance metrics. Study Two extended these findings by evaluating participants across two days of practice in each condition (four days total). Together, the results of the present dissertation advance both the theoretical understanding and practical guidance of VR training for motor skills and provides a foundation for future research aimed at developing effective, evidence-based VR interventions for diverse populations and applied domains.

Keywords: virtual reality; human performance; motor skill; motor learning

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GLOSSARY OF TERMS

Field of View: The visual angle the viewer can see without head rotation (Cruz-Neira et al., 1992).

Immersion: A psychological construct "characterized by perceiving oneself to be enveloped by, included in, and interacting with an environment that provides a continuous stream of stimuli and experiences" (Witmer & Singer, 1998, p. 227).

Immersive Virtual Reality (IVR): Technologies that change the user's perspective with their head movements, thus maintaining complete immersion in the virtual environment (e.g., Oculus, HTC Vive).

Non-Immersive Virtual Reality (NIVR): Technologies that involve two-dimensional or three-dimensional technology that do not maintain the virtual environment with user movement, (i.e., the user is aware of, or can visually recognize, the screen or workstation) (Adamovich et al., 2009; Radianti et al., 2020).

Semi-Immersive Virtual Reality: Technologies that project a stereo image of a three-dimensional scene onto a monitor using perspective projection coupled with the head position of the observer, allowing users to perceive a different reality while maintaining a connection to their physical surroundings without utilizing physical movement (Ware et al., 1993).

Transfer of Learning: The "influence of prior learning on the learning of a new skill or the performance of a skill in a new context" (Magill & Anderson, 2021, p. 307).

Virtual Reality: Technology "that involves real-time simulation of an environment, scenario, or activity that allows" single- or multi-user "interaction via multiple sensory channels" (Adamovich et al., 2009, p. 29; Burdea, 2003).

INTRODUCTION

Rapid advancements in virtual reality technology have stimulated increased commercial production of virtual reality headsets, such as the Oculus Quest and HTC Vive, for recreational use. However, virtual reality technology's increasing ability to mimic real-world experiences has sparked heightened interest in its utility beyond recreational entertainment with it now being recognized as an important tool for teaching and learning. Companies like Sony, Samsung, and Google have made significant investments in virtual reality technology over the past fifteen years. Also in that time, a variety of fields, including computer science, engineering, clinical medicine, rehabilitation, and neuroscience, have experienced substantial increases in virtual reality research interest (Cipresso et al., 2018). Despite the ever-growing attraction to this technology, many questions remain unanswered regarding its efficacy as a training tool and the underlying mechanisms for its effectiveness. The following literature review begins with an overview of the historical evolution of virtual reality. It then provides a working definition of virtual reality as it stands today. Following this, an examination of the research on virtual reality for motor skill learning is provided, highlighting both its effectiveness and shortcomings. Finally, this review of the literature will conclude with an overview of the current state of theoretical explanations for virtual reality's effectiveness.

The History of Virtual Reality

Recent interest from high-profile investors and a substantial increase in commercial use of virtual reality (VR) headsets suggest this is a new breakthrough in technological innovation (Castelvecchi, 2016); Cipresso et al., 2018; Luckerson, 2014). However, the history of VR spans more than fifty years with the technology experiencing many evolutionary iterations in that period. From its inception, military interest has incentivized the advancement of VR technology, but the addition of multinational companies such as Nintendo and Meta generated low-cost, game-based hardware and software alternatives which are commonly used today.

The Origins of Virtual Reality

Although the modern use of VR technology largely results from the substantial advancements of the past decade, the origin of VR can be traced as far back as the 1960s. In 1960, the first ever head-mounted display (HMD), the Telesphere Mask (Figure 1), was patented. While it lacked the motion tracking capabilities available today, the device did feature a wide, three-dimensional (3D) stereoscopic image and stereo sound.

Figure 1. Telesphere Mask circa 1960.

One year later, in 1961, the first motion tracking HMD (i.e., Headsight) was developed. Made for assisting military personnel in the remote viewing of hazardous situations, Philco Corporation's invention featured a video screen for each eye and a magnetic tracking system linked to a closed-circuit camera. Headsight was among the first devices capable of tracking user head movement (Uruthiralingam & Rea, 2020). It could display video footage via a remotely mounted camera that changed angles according to the user's head position. However, this video footage lacked interactivity, and the HMD itself limited user movement due to its size and weight. Additionally, although the development of Headsight marked the foundation of modern HMDs, it operated via a remote camera and did not integrate with computers or any other image generation technology like the HMDs of today. Although limited in its capabilities, this technology serves as the keystone to modern interactive HMD systems.

At the same time these first HMDs took shape, American filmmaker Morton Heilig developed and patented Sensorama (Figure 2), a screen-projection based device. This simulated experience allowed participants to virtually “ride” a motorcycle through the streets of Brooklyn, complete with auditory, olfactory, and haptic feedback (Heilig, 1962). Sensorama featured a booth-like seat capable of vibrations, and utilized stereoscopic color display, fan-generated wind, odor emitters, and stereo-sound to create a multisensory experience for the user. Despite Sensorama’s impressiveness, its high production cost and Heilig’s inability to obtain adequate financial backing halted any further advancements of the technology.

Figure 2. Sensorama circa 1962.

In 1965, despite the typewriter being the most direct computer input of the time, Ivan Sutherland (1965) conceptualized, but never manufactured, a future technology he called a “looking-glass” display that could sense body position and interpret eye movements, allowing the user to have a realistic virtual experience. Three years later, Sutherland proposed the idea of a 3D HMD that could change the user’s perspective image as they moved through a physical environment (Sutherland, 1968). Though he acknowledged the importance of stereo presentation in creating the illusion of a 3D image, Sutherland hypothesized it was more important that the virtual image change with the user's movement through the environment in exactly the same way that the image of a real object would within the physical environment (Sutherland, 1968). Sutherland understood from the early conception of this new technology that the physics of the virtual world needed to match the physics of the real-world to optimize the experience of the user. Building on these ideas, Sutherland and his students attempted to develop the first HMD connected to a computer. Although this technology (i.e., Sword of Damocles, Figure 3) featured basic computer-generated graphics, the device was heavy and rather uncomfortable for the user. While Sutherland perfectly envisioned future VR capabilities in 1968 when he described the ideal user interactivity and immersion within a virtual environment, several years would pass before technological advancements enabled his ideas to become reality.

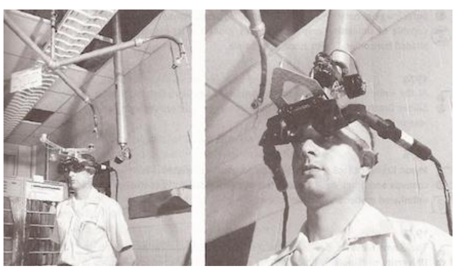

Figure 3. Sword of Damocles circa 1968.

While the 1970s saw little progress for HMDs, screen-based virtual environments experienced continued pivotal advancements. It was during this time that Myron Kreuger developed Videoplace, a computer-based virtual environment that projected a participant's live image onto a video screen to create the feeling of interactivity (Krueger et al., 1985). Unlike its HMD predecessors, Videoplace did not require the user to wear equipment, allowing them to interact more freely with the projected virtual environment. However, despite this technological breakthrough, Videoplace remained an experimentally focused invention. It was not until 1979, that the United States military implemented the Vital helmet, marking one of the first times VR technology was used in an applied setting (Virtual Reality Society, n.d.). Over a decade after the invention of Sword of Damocles (Sutherland, 1968), the Vital helmet utilized a head tracker to allow fighter pilots to see primitive computer-generated images. While using the device, the user was able to view and manipulate controls in the cockpit while simultaneously viewing 3D images of the outside world which allowed pilots to train for future missions. However, the weight of the device and low-quality visuals limited its functionality.

Following the development of the Vital helmet, the following decade of the 1980s marked the beginning of widely distributed, commercially available VR technologies. First, in 1982, the finger-tracking "Sayre" gloves were invented (Sturman & Zeltzer, 1994). Sayre gloves connected to a computer and utilized optical sensors to detect finger movements. This evolution in technology paved the foundation for the data gloves used today. However, Sayre gloves were limited to motion tracking and were not capable of providing proprioceptive feedback like modern data gloves, such as HaptX, which provide advanced haptic feedback in real-time. Then, in 1987, founder of the Visual Programming Lab (VPL) Jaron Lanier coined the term "virtual reality" and developed the EyePhone HMD (Figure 4). VPL's EyePhone was an immersive headset and glove combination that utilized hand to head tracking to create immersion for the user within a computer simulation (Stone, 2016). While utilizing the EyePhone, users could view and interact with objects in the virtual world but were limited to a 108° field of view rather than the 360° visual experience immersive technology utilizes today. As intended, the EyePhone successfully created an HMD immersive virtual experience that allowed users to more naturally interact with a computer-generated environment, but its $250,000 price tag and limited practical application resulted in a rapid decline in investor interest.

Figure 4. EyePhone circa 1990s.

By the late 1980s, VR technology was making rapid advancements that would continually evolve into the 1990s and early 2000s. For instance, in 1992, researchers at the University of Illinois developed the Cave Automatic Virtual Environment (CAVE) system (Figure 5). The CAVE system introduced a new VR interface by surrounding the user with display screens, forming a cube-like environment which created an immersive experience without the need for wearable technology (Cruz-Neira et al., 1992). The CAVE is still in use today, primarily for research purposes, as it can accommodate physical limitations, such as wheelchair access, which limit the use of HMDs in some practical settings (Genova et al., 2022). However, its large size and high cost limit its commercial appeal and widespread practical application.

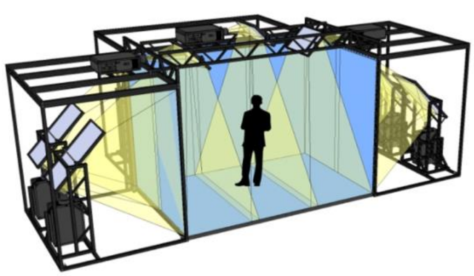

Figure 5. VisCube CAVE Immersive 3D Display.

Additionally, in the early 1990s, VR technology found its way into the video gaming industry, where it is still widely used today. As of 2022, virtual reality in gaming had an estimated market size of over $20 billion and is estimated to grow an additional 22.7% from 2023 to 2030 (Grand View Research, 2023). By 1995, gaming companies such as Nintendo and Sega both had gaming consoles capable of 3D imagery, motion tracking, and stereo sound. While 3D imagery technology would continue to develop at a rapid pace, the next major advancement in HMDs would take more than a decade to emerge. Most notably, in 2010, the initial Oculus Rift HMD was prototyped, serving as the catalyst for immersive virtual reality as it is known today. Since the Oculus Rift was initially introduced, several immersive VR systems have been developed and released including the HTC Vive, PlayStation VR, and Oculus Quest series. These technologies create a fully immersive experience by utilizing a combination of HMDs and hand controllers as well as motion tracking which facilitates high levels of interactivity. Several mixed reality technologies have also emerged such as the Microsoft HoloLens, Magic Leap, and Apple Vision Pro which also use a combination of HMDs, hand controllers, and motion tracking to create semi-immersive experiences. Unlike its predecessors, today's Meta (i.e., formerly Oculus) Quest (Figure 6) is capable of tracking head and body movements and maintaining a 3D virtual experience without the use of external trackers. HMDs are now more powerful, comfortable, and affordable than ever before, facilitating their use across a wide range of fields including education (Estep & Clark, 2022; Kavanagh et al., 2017; Perez-Valle & Sagasti, 2012), clinical medicine (Bani Salameh et al., 2024; Frederikson et al., 2020; Pulijala et al., 2018), rehabilitation (Lee et al., 2020; Saldana et al., 2020), military training (Harris et al., 2023; Oberhauser et al., 2018), and sport (Markwell et al., 2023; Michalski et al., 2019b).

Figure 6. Meta Quest 3 circa 2023.

Defining Virtual Reality Today

Numerous research papers spanning several disciplines ranging from clinical medicine to military training to sport skill development have explored VR technology over the past twenty-five years (Cipresso et al., 2018). However, one recurring challenge within the current body of research is the inconsistency of defining "virtual reality." Broadly, VR can be defined as technology "that involves real-time simulation of an environment, scenario, or activity that allows" single- or multi-user "interaction via multiple sensory channels" (Adamovich et al., 2009, p. 29; Burdea, 2003). However, a distinction should be made between immersive virtual reality (IVR) and non-immersive virtual reality (NIVR).

Immersion is a psychological construct "characterized by perceiving oneself to be enveloped by, included in, and interacting with an environment that provides a continuous stream of stimuli and experiences" (Witmer & Singer, 1998, p. 227). Just as Sutherland (1968) first proposed, IVR technologies today change the user's perspective with their head movements, thus allowing and maintaining complete immersion in the virtual environment. IVR technologies achieve a full 360° visual experience by allowing the viewer to easily and quickly alter position while maintaining the correct orientation of the virtual environment (Cruz-Neira et al., 1992). Additionally, IVR technologies generally incorporate built-in audio and a full-body kinesthetic experience through advanced head and hand tracking. Present commercially available examples of IVR systems include the Oculus and HTC Vive HMDs as well as the CAVE system.

In contrast, NIVR technologies have a less than 360° visual experience and involve two-dimensional (2D) or 3D technology that do not maintain the virtual environment with user movement (Adamovich et al., 2009). While using these systems, the user is aware of, or can visually recognize, the screen or workstation (Radianti et al., 2020). Current NIVR technologies primarily utilize computer screens or video projections to present to the user (Figure 7).

Figure 7. Examples of non-immersive technologies.

In addition to the IVR and NIVR classifications, a third distinction can be made. "Semi-immersive" systems (Figure 8). If immersion is thought of as a continuum anchored by non-immersive systems on one end and completely immersive systems on the other end of the continuum, semi-immersive systems exist somewhere between the two. These technologies project a stereo image of a 3D scene onto a monitor using perspective projection coupled with the head position of the observer (Ware et al., 1993). Typically used more for educational purposes, the user experience is mainly visual as the technology does not track user movements in the same way an immersive system does. Instead, semi-immersive technologies utilize additional equipment like a steering wheel or computer keyboard, or a computer mouse to manipulate user interactivity with the virtual environment. This allows users to perceive a different reality while maintaining a connection to their physical surroundings.

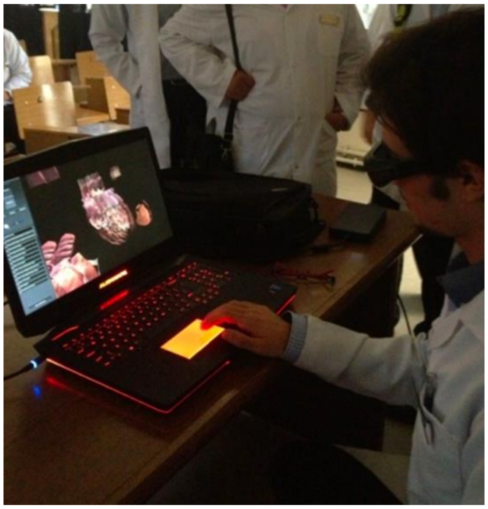

Figure 8. Semi-immersive environment (Alfalah et al., 2019).

Although the term “virtual reality” is broadly used in the current body of literature to describe various technologies, distinguishing between non-immersive and fully immersive environments is crucial to understanding how this technology is applied across different disciplines. While this section has established key definitions and classifications, questions remain regarding the effectiveness of VR in practical settings. The following section will evaluate VR in various learning environments and its impact on skill acquisition and retention.

Virtual Reality and Learning

Bloom’s Taxonomy (Figure 9) is a widely used framework for classifying educational learning objectives. Specifically, the taxonomy specifies student learning outcomes while distinguishing between higher-order and lower-order cognitive skills (Adams, 2015). VR technology enables students to experience different levels of Bloom’s Taxonomy simultaneously by exposing the learner to new information and affords opportunities to evaluate concepts, apply theories, analyze problems, acquire and apply knowledge to real-world (RW) settings, and engage in critical reflection (Fowler, 2015). Rather than simply discussing RW behaviors and settings, VR allows users to *experience* those settings and behaviors firsthand. For example, rather than viewing static images or reading hypothetical scenarios, an undergraduate marketing class can go on a "virtual field trip" to a grocery store, facilitating rich discussions about what they view on the shelves in real-time (Estep & Clark, 2022). Similarly, rather than being limited to a single rehabilitation center, in-patient rehabilitation patients can use VR to practice navigating real-world environments while remaining in the safety of the facility and under the supervision of the practitioner.

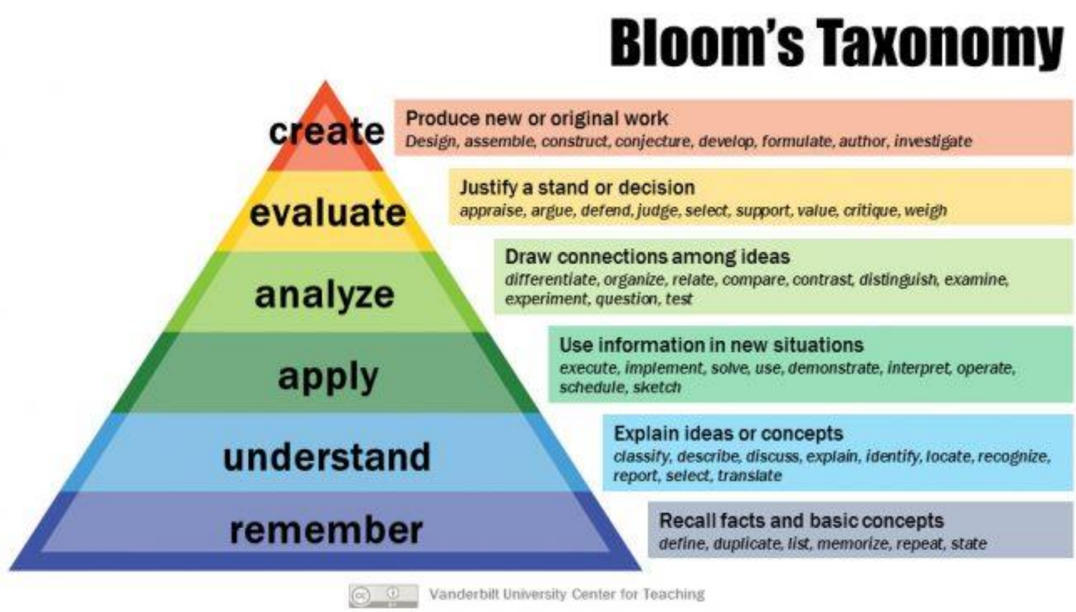

Figure 9. Bloom's Taxonomy. An educational framework that can be used to develop learning outcomes (Armstrong, n.d.).

Educators use VR to facilitate RW transfer of practical skills, increase access to limited resources, and enhance the effectiveness of distance learning (Kavanagh et al., 2017). VR can be used to simulate classroom experiences that would otherwise be impossible such as visiting 16th century Spain (Perez-Valle & Sagasti, 2012) or practicing fire drills with actual hazards (Kavanagh et al., 2017). VR can also bring expensive, hazardous, or finite resources like laboratory equipment and live patients into the classrooms with ease, which can also provide comparable classroom experiences for distance-learners (Kavanagh et al., 2017). Traditional learning tools, like video recordings, typically focus on just one or two sensory modalities at one time, but VR allows for the concurrent use of visual, auditory, and kinesthetic modalities. Allcoat and von Mühlenen (2018) investigated the effects of VR practice on learning and emotional response by randomly assigning first-year psychology students to one of three learning conditions: traditional, video, or VR. All three conditions utilized the same text and three-dimensional (3D) model of a plant cell. The VR group utilized the HTC Vive HMD to see and interact with the model and accompanying text. In this condition, participants could interact with the model by highlighting individual cell parts, changing the size of the model, or rotating it. In the video group, participants were shown a two-dimensional (2D) video recording taken from the HTC Vive that matched the VR condition. The traditional group were shown screenshots of the 3D model with the accompanying text presented to them on a computer screen using a PDF document. The results showed that students scored significantly higher on learning assessments following the VR study intervention compared to those who utilized the 2D video, while scores did not statistically differ from those in the traditional group (Allcoat & von Mühlenen, 2018). While video recordings may help learners with visualization, they are passive learning tools. In contrast, VR technology promotes active learning by enabling users to interact directly with the virtual environment (Allcoat & von Mühlenen, 2018). This direct interaction enables them to apply, analyze, and evaluate new concepts all at the same time, thus simultaneously engaging them in levels of Bloom's Taxonomy that would traditionally be experienced in a hierarchical order simultaneously (Fowler, 2015).

VR technology has the unique ability to offer solutions to multiple issues impacting learner performance simultaneously, but its most critical advantage is its ability to simulate explorations that are impractical, unfeasible, or too dangerous to experience in reality (Kavanagh et al., 2017). For instance, using VR technology international travel for public school children becomes possible, flight crews can practice aircraft fire drills, pilots can practice emergency landing procedures, surgeons can rehearse complicated pre-operation techniques, and VR allows workers at chemical processing plants can practice emergency fire extinguishing procedures without the risk of physical injury.

Virtual Reality and Motor Skill Learning

Broadly, motor skill learning is defined as improvements in motor performance resulting from practice (Magill & Anderson, 2021, p. 263). One way to assess motor skill learning is through a test of motor skill transfer, which occurs when previously learned skills are applied within a new context or applied to a new skill. In research, transfer of learning refers to the "influence of prior learning on the learning of a new skill or the performance of a skill in a new context" (Magill & Anderson, 2021, p. 307). The previously learned skill can have a positive (i.e., facilitative), negative (i.e., debilitative), or zero (i.e., neutral) effect on learning. While transfer intervals can be somewhat arbitrary, assessment should take place at least twenty-four hours following the conclusion of practice to test of motor skill transfer (Trempe & Proteau, 2010). If VR is an effective tool for motor skill learning, the learner should demonstrate positive transfer to the RW task following practice in VR. Although VR practice has been studied across various skills and contexts, including clinical medicine (Cevallos et al., 2022; Sommer et al., 2021; Torkington et al., 2001), rehabilitation (Adamovich et al., 2009; Laver et al., 2017; Wiley et al., 2022), military training (Bhagat et al., 2016; Harris et al., 2023; Liu et al., 2018;

Oberhauser et al., 2018), and sport (Gray, 2017; Markwell et al., 2023; Michalski et al., 2019b; Rauter et al., 2013; Tirp et al., 2015), many of these studies do not include measures of motor skill transfer of learning (Cevallos et al., 2022; Harris et al., 2023; Oberhauser et al., 2018; Torkington et al., 2001). The following sections summarize the available research on motor skill transfer and how it has been investigated across a range of disciplines.

Virtual Reality and Clinical Medicine

VR presents a cost- and time-effective modality of training for medical resident educators (Cevallos et al., 2022). A recent national comparison of operative outcomes between new and experienced surgeons concluded worse outcomes were more closely related to the context of care delivery and complexity of the patient, rather than surgeon experience (Kelz et al., 2021). Thus, it is critical that resident practitioners be exposed to a wide variety of medical contexts and patients. VR training environments afford the opportunity for a broader range of practice scenarios compared to traditional clinical training environments. Moreover, the task characteristics are more easily modifiable in VR, making VR an appealing training tool for novices and experienced practitioners alike.

For instance, novices who trained using the Minimally Invasive Surgical Trainer in Virtual Reality (MIST-VR) experienced quantifiable changes in performance that positively transferred to the RW operative task (Torkington et al., 2001). Additionally, surgical residents who trained in VR performed gallbladder dissection faster and more safely than non-VR-trained residents (Seymour et al., 2002). Notably, the non-VR-trained residents were found to be nine times more likely to transiently fail to make progress, and five times more likely to injure the gallbladder or burn nontarget tissue, compared to the VR-trained residents (Seymour et al., 2002). These findings suggest VR training can improve RW surgical performance and improve patient safety. The findings demonstrate the potential value VR provides as a training tool for both novice and resident practitioners.

The COVID-19 pandemic, and resulting social distancing guidelines, sparked new challenges for aspiring and active healthcare professionals. As a result, many turned to VR for hands-on experience. In a study by Sommer et al. (2021), sixty medical students were randomly assigned to either a training group or control group. Over the course of two weeks, the training group underwent a comprehensive curriculum training involving a total of forty-eight different simulator tasks at various difficulty levels in VR while completing a laparoscopic cholecystectomy. Following this structured VR-simulator curriculum, students significantly improved their visual spatial imagination, surgical performance, and operative completion time (Sommer et al., 2021), providing further support for the use of VR simulation for training surgical skills. While these results are promising, the value of VR training for clinical professionals may extend beyond the mere acquisition and development of task-specific motor skills.

Psychological factors, such as self-confidence, have been positively correlated with instructor-assessed performance of students in residency (Geoffrion et al., 2013). For example, in recent studies, IVR training was found to have a significant positive impact on self-confidence (Bani Salameh et al., 2024; Pulijala et al., 2018). Pulijala and colleagues (2018) demonstrated that a single 45-minute training session in IVR resulted in significantly positive changes in the self-confidence of dental students in residency. Nursing students also displayed significantly increased self-confidence following a three-week IVR intervention (Bani Salameh et al., 2024). These results suggest IVR can have both an acute and chronic positive effect on medical students' self-confidence. Additional positive psychological outcomes have been demonstrated across other practitioner populations such as patient rehabilitation.

Virtual Reality and Rehabilitation

Over the past decade, rehabilitation and clinical neurology have ranked amongst the top ten leading subject categories for VR research (Cipresso et al., 2018). Studies have explored VR use in various rehabilitation settings including injury rehabilitation, neurorehabilitation, and psychotherapy. Stroke patients with resulting neurological deficits often struggle with muscle strength and coordination loss. While not necessarily superior to traditional methods, VR-based interventions have been found to be effective for improving both cognitive and motor function following stroke (Laver et al., 2017; Wiley et al., 2022). Patients in a VR rehabilitation group made significant gains at both the impairment and functional levels, as measured by assessments of motor recovery and measures of disability, respectively (Adamovich et al., 2009). Additionally, stroke patient performance improved immediately following a three-week NIVR training program as well as twelve-weeks post training (Bao et al, 2013). These findings demonstrate VR's effectiveness in improving both cognitive and motor function, showcasing its value as a rehabilitation tool.

Like the physical challenges accompanying a stroke, individuals with cerebral palsy (CP) often experience difficulty controlling and coordinating voluntary muscle movements. In a review of the existing literature on sensorimotor training in VR, Adamovich and colleagues (2009) determined that when compared to traditional therapy, patients who utilized VR displayed a greater range of motion and longer hold times for stretch. Furthermore, patients who practiced with VR improved their performance on gait speed, endurance, and standing balance measures (Adamovich et al., 2009). In addition to these findings on rehabilitation protocols, patients who utilized VR therapy reported greater levels of enjoyment (Adamovich et al., 2009) and increased satisfaction with rehabilitation (Wiley et al., 2022), which may be important factors affecting rehabilitation protocol adherence. Further underscoring this, a recent review found enjoyment to play a mediating role in exercise rehabilitation adherence, highlighting its influence on patient motivation (Teo et al., 2022).

In addition to positive patient outcomes, VR possesses benefits for rehabilitation practitioners as well. VR training environments can be systematically graded in terms of both speed and complexity (Adamovich et al., 2009). They also provide practitioners with instant feedback and easily modifiable difficulty levels for the patient (Wiley et al., 2022). By coupling VR training with therapist oversight, practitioners can facilitate a more safe and systematic training environment for their patients (Adamovich et al., 2009).

VR research in rehabilitation settings highlights the dual value of VR technology for patients and practitioners. For patients, VR interventions provide more engaging alternatives to traditional therapy while effectively improving functional outcomes (Adamovich et al., 2009; Bao et al, 2013; Laver et al., 2017; Wiley et al., 2022). For the practitioner, VR interventions are highly customizable and provide real-time feedback which improves the working environment for the rehabilitation specialist (Adamovich et al., 2009; Wiley et al., 2022). Together, VR is a valuable tool for supporting custom tailored interventions that meet individual patient needs while at the same time improves the functional capabilities of the practitioner.

Virtual Reality and Military Training

In 2017, the House Armed Services Committee reported "nearly four times as many members of the military died in training accidents [compared to those which] were killed in combat," with many of those deaths credited to aviation mishaps (No. 202-225-2539, p. 4). Thus, the pursuit to develop safe and effective military training protocols persists with the goal of reducing the loss of life as a result of training errors. In military settings, VR training typically entails some type of physical simulation technology capable of simulating actual vehicles and real soldier or combat environments (Liu et al., 2018). One such example is aviation simulators (Figure 10), which are commonly used to engage in some level of flight training by providing the learner with a virtual representation of a RW cockpit experience (Oberhauser et al., 2018).

Figure 10. Frasca Full Flight Simulator.

While traditional military training is often costly and long-lasting in duration, VR can train military personnel using virtually simulated battlefield environments at a fraction of the cost (Liu et al., 2018). As a result, VR simulation is commonly used for live fire training in military settings. In one recent study, Harris and colleagues (2023) demonstrated the ability of a VR room clearing simulation to elicit high feelings of presence in the user. Furthermore, interactive virtual systems have been found to positively affect learning outcomes, performer motivation, and live fire performance (Bhagat et al., 2016). VR simulation has also been employed to optimize the acquisition and retention of military medical skills, but results have been mixed. For instance, there is evidence for the effectiveness of VR training systems for relearning and maintenance of surgical skills (Siu et al., 2016), a recent review concluded the current body of literature lacked evidence for the benefit of virtual and other extended realities as a means of training open trauma, emergency surgery or improving soldier outcomes (Mackenzie et al., 2022).

To summarize, VR simulation is commonly used in military settings for flight (Oberhauser et al., 2018), live fire (Bhagat et al., 2016; Harris et al., 2023), and medical (Siu et al., 2016) training. It has been shown to facilitate greater task-specific problem-solving by simulating various unexpected scenarios, such as equipment malfunctions and adverse weather conditions (Lele, 2013; Liu et al., 2018), contributing to its widespread usage in military sectors. However, VR as a mechanism for positive transfer of learning to RW military tasks still requires further evaluation (Cross et al., 2023). Hardware constraints, deficient research designs, and reporting bias limit the available empirical evidence for the effectiveness of VR simulation for RW military skills (Cross et al., 2023; Mackenzie et al., 2022). Therefore, larger, more rigorously designed studies that include measures of skill transfer to RW military settings are needed.

Virtual Reality and Sport

VR research in sport settings is relatively new compared to clinical domains, and few studies in the existing literature include measures of RW transfer (Michalski et al., 2019a). However, the existing literature does provide preliminary evidence that practicing in VR positively transfers to RW sports such as rowing (Rauter et al., 2013), dart-throwing (Tirp et al., 2015), baseball (Gray, 2017), table-tennis (Michalski et al., 2019b), and golf putting (Markwell et al., 2023). Following four separate days of training, recreational rowers who trained using a scull rowing simulator (Figure 11) achieved similar performance improvements as those trained on the water (Rauter et al., 2013). They also displayed positive transfer to the RW motor skill (Rauter et al., 2013). Similarly, competitive high school baseball players showed significantly greater improvement than all other test groups on most laboratory-based measures of performance, and improved their RW performance, following a six-week adaptive VR training protocol (Gray, 2017). While both Rauter et al. (2013) and Gray (2017) utilized complex simulations combined with RW equipment (i.e., rowing machine and baseball bat), Tirp et al. (2015), Michalski et al. (2019b), and Markwell et al. (2023) achieved similar results using only VR equipment.

Figure 11. Scull rowing simulator (Rauter et al., 2013).

For example, after seven sessions using the HTC Vive, an immersive HMD, participants improved their RW table-tennis performance (Michalski et al., 2019b). Similarly, using the Oculus Quest 2, another immersive HMD comparable to the HTC Vive, participants improved their RW golf putting performance (Markwell et al., 2023). Participants also improved their RW dart-throwing accuracy and enhanced their quiet eye duration (QED) from pre- to post-test after three separate training sessions utilizing the Microsoft Xbox Kinect, a NIVR technology (Tirp et al., 2015). While another study (Drew et al., 2020) investigating VR training for dart-throwing demonstrated contradictory results compared to those reported by Tirp et al. (2025). Specifically, the results reported by Drew et al. (2020) demonstrated that the VR-trained group performed significantly worse on measures of accuracy compared to the RW-trained group. However, it is important to note that the study conducted by Drew et al. (2020) did not include a transfer of learning assessment. Notably, in Tirp et al.'s 2015 study, Michalski et al.'s 2019 study, and Markwell et al.'s 2023 study, performance improvements did not statically differ between the VR and RW-trained groups. These results suggest training in VR may be equally effective as traditional training, though not superior.

Virtual Reality for Open and Closed Motor Skills

Broadly, motor skills can be classified as either open (i.e., unpredictable, changing, and externally paced) or closed (i.e., predictable, consistent, and self-paced) (Wang et al., 2013). Practice variability (i.e., practice conditions that are varied or continually changing) is crucial for successfully performing both types of skills (Lee & Magill, 1985). Utilizing variability in practice, also referred to as interleaved practice, forces the learner to actively retrieve and re-encode information, increasing the likelihood of long-term retention and transfer (Rohrer & Taylor, 2007). One key strength of VR is its ability to easily incorporate practice variability, particularly when RW variability would be unsafe (e.g., hostage scenarios, machinery malfunctions, aviation mishaps, etc.) or prohibitively expensive (e.g., maritime operations, motorsports, large-scale project planning, etc.).

Research has shown positive transfer from VR practice to RW performance in both closed skills (Markwell et al., 2023; Tirp et al., 2015; Torkington et al., 2001) and open skills (Gray, 2017; Michalski et al., 2019b; Rauter et al., 2013). Interestingly, in one study utilizing immersive VR to facilitate practice variability, participants responded to randomized table tennis shots stroked by a virtual tennis player (Streuber et al., 2012). In this study, Streuber and colleagues (2012) observed spontaneous action coupling, the coupling of specific visual information and motor responses, in the participants' kinematics, providing preliminary evidence that VR training may improve decision-making and response preparation. However, despite these findings, VR training for RW decision-making and response preparation, particularly for motor skills that are inherently unpredictable, remains underexplored. This highlights the need for further research involving motor skills with varying characteristics and classifications.

Comparing the Effectiveness of Immersive and Non-Immersive Technologies

As detailed previously, the current literature poorly distinguishes between IVR and NIVR when defining these environments. While both have demonstrated positive transfer to RW tasks independently (Adamovich et al., 2009; Bao et al, 2013; Gray, 2017; Michalski et al., 2019b; Rauter et al., 2013; Tirp et al., 2015; Torkington et al., 2001), few studies have compared IVR and NIVR environments directly. Of the studies that have made this comparison, several have focused on immediate performance assessment rather than long-term assessments of motor learning (Kiper et al., 2020; Plechatá et al., 2019; Ventura et al., 2019). Among the studies focusing on motor performance, results have been mixed regarding whether NIVR or IVR environments are more effective (Frederikson et al., 2020; Juliano & Liew, 2020; Polechoński et al., 2024). Research findings illustrating these mixed results are discussed in the following paragraphs.

Juliano and Liew (2020) investigated the transfer of learning effects between HMD-VR and computer screen learning conditions. Measures of motor skill acquisition (i.e., assigned condition performance), motor skill transfer (i.e., opposite condition performance), simulator sickness, and presence were collected. Interestingly, participants who learned the skill in the HMD-VR condition were not able to successfully transfer performance when they were tested on a computer, but the participants who learned the skill in the computer screen condition *improved* performance in the HMD-VR environment (Juliano & Liew, 2020). In other words, the NIVR condition resulted in greater positive transfer to the IVR environment, though the transfer was to another simulation rather than a RW task. By point of comparison, participants practicing in an IVR environment using the HMD did not demonstrate positive transfer of learning when tested in a NIVR environment on a computer.

Similarly to the findings reported by Juliano and Liew (2020), when investigating cognitive load and performance during a simulated surgical procedure, Frederikson and colleagues (2020) found an NIVR condition yielded significantly better practice performance than the IVR condition. However, the IVR group reported experiencing higher cognitive load, which is more reflective of the RW conditions experienced by surgeons (Frederikson et al., 2020). These findings are important because they highlight a potential trade-off between NIVR and IVR practice conditions. If the goal of practice is to build learner confidence and procedural knowledge, especially in the early stages of learning, then these findings would suggest NIVR practice conditions may be most appropriate. However, if the goal is to prepare learners for RW decision-making and adaptability, particularly in later stages of learning, then these findings suggest IVR practice conditions may provide the learner with more realistic RW scenarios.

Notably, participants in the most recent study to investigate both NIVR and IVR conditions reported significantly higher satisfaction and feelings of flow, defined by researchers as an optimal mental state characterized by full engagement with the activity being performed, in the IVR condition (Polechoński et al., 2024). Flow has been associated with higher perceptions of performance, which can in turn enhance the learner's perceptions of the learning experience (Csikszentmihalyi, 1990; Ryan & Deci, 2000). These findings suggest IVR training environments may be more effective at facilitating psychological engagement than NIVR training environments, which has been shown to enhance motor skill learning, retention, and transfer (Lohse et al., 2016). It is important to point out that Polechoński et al. (2024) did not measure participants' actual motor skill performance. And while there is value in IVR's ability to elicit RW affective responses, definitive conclusions about motor learning cannot be made without measures of transfer, especially considering that practice performance is often misleading (Magill & Anderson, 2021). For example, Seymour and colleagues (2002) conducted a study comparing VR and traditional training conditions for surgical skill acquisition. Although there were no significant differences in early practice performance between the VR and traditional training groups, the VR group demonstrated significantly better retention and transfer when tested up to two weeks following the initial training session (Seymour et al., 2002).

To summarize, both NIVR and IVR training conditions have shown positive transfer to RW tasks independently (Adamovich et al., 2009; Bao et al, 2013; Gray, 2017; Rauter et al., 2013; Tirp et al., 2015; Torkington et al., 2001; Michalski et al., 2019b), but direct comparison research remains limited. The available body of work comparing these two environments has focused primarily on clinical assessments (Kiper et al., 2020; Plechatá et al., 2019; Ventura et al., 2019), rather than direct evaluation of motor performance. Even studies that include motor behavioral measures tend to emphasize cognitive (e.g., cognitive load) or affective (e.g., motivation, engagement) outcomes over motor skill acquisition and learning. The limited number of available publications using these various metrics have produced mixed results (Frederikson et al., 2020; Juliano & Liew, 2020; Polechoński et al., 2024). Therefore, further research is needed to effectively compare IVR and NIVR environments.

Summary of Research Findings

To date, VR practice has been studied across many motor skills and contexts, ranging from clinical medicine, rehabilitation methods, military training to sport. Clinical research has shown VR's effectiveness in training technical skills in surgical residents (Torkington et al., 2001), improving operative outcomes (Seymour et al., 2002), and positively impacting trainee self-confidence (Bani Salameh et al., 2024; Pulijala et al., 2018). In rehabilitation settings, VR has been shown to improve both cognitive and motor function in stroke patients (Adamovich et al., 2009; Bao et al, 2013; Laver et al., 2017; Wiley et al., 2022) and individuals with CP (Adamovich et al., 2009). Patients who utilized VR during their rehabilitation have also reported greater levels of enjoyment (Adamovich et al., 2009) and increased satisfaction with the rehabilitation process (Wiley et al., 2022). In military settings, VR can be used to simulate real soldier and combat scenarios such as cockpit operations, equipment failures, or adverse weather conditions (Liu et al., 2018), and facilitating greater task-specific problem-solving (Lele, 2013; Liu et al., 2018). In sport settings, VR training has been shown to effectively transfer motor skills to RW rowing (Rauter et al., 2013), dart-throwing (Tirp et al., 2015), baseball (Gray, 2017), table-tennis (Michalski et al., 2019b), and golf putting (Markwell et al., 2023). However, despite NIVR and IVR training conditions demonstrating positive transfer to RW tasks independently (Adamovich et al., 2009; Bao et al, 2013; Gray, 2017; Rauter et al., 2013; Tirp et al., 2015; Torkington et al., 2001; Michalski et al., 2019b), direct comparison research remains limited with mixed results (Frederikson et al., 2020; Juliano & Liew, 2020; Kiper et al., 2020; Plechatá et al., 2019; Polechoński et al., 2024; Ventura et al., 2019). Taken altogether, these findings highlight the need for further, more targeted research to facilitate effective comparison of IVR and NIVR training environments.

Theoretical Explanations

The rationale for employing VR in motor skill learning is grounded in its potential to improve RW skill performance. Transfer of learning theories are central to understanding *why* VR can be an effective tool for motor skill acquisition. Research across multiple levels of analysis have been conducted to explore the underlying mechanisms regarding the transfer of learning from VR to the RW. Therefore, the following section reviews key theoretical perspectives that explain how VR may support RW skill development. These theoretical foundations can best be organized into neural, psychological, cognitive, and behavioral explanations. Each of these explanations will be reviewed in the subsections that follow.

Neural Explanations

Research investigating the neural basis for behavior change focuses on the brain's responses and adaptations to VR stimuli. Utilizing functional magnetic resonance imaging (fMRI), Bao and colleagues (2013) found similar activation maps between healthy participants and stroke patients following a twelve-week NIVR intervention. Comparable primary sensory motor cortex, supplementary motor area, and cerebellum activation was observed across all participants, suggesting NIVR's facilitation of functional neuroplasticity may be related to primary sensorimotor cortex reorganization (Bao et al, 2013). In a more recent study, Keller and colleagues (2020) found increased cortical volume of subcortical and cortical regions following a therapeutic NIVR intervention for upper limb motor activity. Increases in grey matter volume were also observed in subcortical structures including the hippocampus, rostral cingulum, and caudatum, all of which are involved in the learning process (Keller et al., 2020). Utilizing electroencephalogram (EEG), Kober and colleagues (2021) also found similar brain activation patterns between IVR and RW conditions, but the IVR condition led to a weaker hemispheric lateralization effect. Markwell (2023) provides further evidence to support these similarities, as no differences in neural activity were found between IVR and RW conditions over an extended period of practice. Additionally, resident surgeons who trained using a robot assisted surgery (RAS) device in conjunction with a non-immersive virtual simulator showed significantly lower relative oxygenation changes in the prefrontal cortex with increased practice (Izzetoglu et al., 2021). This finding aligns with previous research demonstrating a relationship between repeated RW task practice and decreased brain activations (Kelly & Garavan, 2005), supporting the idea that repeated VR practice, like RW practice, can lead to optimized brain activation patterns.

Altogether, the current body of literature partially supports the conclusion that brain activation patterns are similar when performing a task in a virtual environment compared to performing the same task in the RW (Bao et al, 2013; Izzetoglu et al., 2021; Kober et al., 2021; Markwell, 2023). However, other studies have found contradictory results, concluding that there are differences in brain activation patterns between VR and RW conditions (Fernández et al., 2017; Pacheco et al., 2017). Fernández and colleagues (2017) utilized a virtual avatar that performed different hand motions for participants to repeat under three conditions: by memory, while watching it on a screen, and while seeing it in VR. Although there were no significant differences in participant EMG activity across conditions, there were significant differences in EEG activity, specifically higher alpha desynchronization while moving the hands in the VR condition (Fernández et al., 2017). Similarly, Pacheco and colleagues (2017) found differences in theta, alpha, beta, and gamma activity in participants going up and down steps across RW and VR conditions. These results suggest that while the physical task may be the same, brain dynamics may be different when performing under RW and VR conditions. Therefore, further research is needed to clarify the conditions under which brain activation patterns are similar or dissimilar between VR and RW environments.

Psychological Explanations

Research investigating the psychological basis for behavior change explores the emotional processes involved in VR experiences. Training in VR has been linked to several positive psychological factors including changes in engagement (Allcoat & von Mühlenen, 2018), enjoyment (Adamovich et al., 2009; Markwell et al., 2023; Wiley et al., 2022), and intrinsic motivation (Markwell et al., 2023).

Following an IVR intervention utilizing the HTC Vive HMD, students reported higher levels of engagement and increases in positive emotions, such as interest, amusement, surprise, and elatedness, compared to students utilizing video or traditional textbook learning methods (Allcoat & von Mühlenen, 2018). This finding is meaningful because previous research has shown that increased engagement during practice improves learning, retention, and transfer of a complex motor skill (Lohse et al., 2016). However, in a more recent study, no statistically significant differences in engagement were found between IVR and RW practice groups (Markwell et al., 2023). Therefore, while engagement may be one psychological factor affected by VR, further research is needed to clarify this relationship.

Another psychological factor highlighted by VR research is enjoyment. Patient populations in particular have been found to rate VR interventions more enjoyable than traditional therapy, even when they are equally effective in terms of motor skill rehabilitation (Adamovich et al., 2009; Wiley et al., 2022). Similarly, participants who practiced golf putting in an IVR training condition reported significantly greater levels of enjoyment compared to those in the traditional training condition, despite there being no significant group differences in motor learning (Markwell et al., 2023). These results are noteworthy because enjoyment has been associated with increases in physical activity levels (Dishman et al., 2005), continued participation in sport (Butcher et al., 2002), and rehabilitation protocol adherence (Pizzari et al., 2002).

In addition to engagement and enjoyment, VR practice has been linked to changes in intrinsic motivation (Markwell et al., 2023). Intrinsic motivation has been suggested as a contributing factor to motor performance and learning (Wulf & Lewthwaite, 2016). Participants in an IVR practice condition reported significantly greater increases in intrinsic motivation on posttest measures than those in the RW practice condition (Markwell et al., 2023). Altogether, these findings underscore the potential of VR to positively influence psychological factors that impact motor learning.

Cognitive Explanations

Research investigating the cognitive basis for behavior change explores the cognitive, rather than emotional, processes associated with VR experiences. Transfer Appropriate Processing (TAP) Theory is a memory-based theory that states the greater the similarity in cognitive processes, such as memory encoding and retrieval activities, between motor skills or performance contexts, the higher the degree of positive transfer of learning will occur (Morris et al., 1977). Generally, VR is highly interactive, which results in the learner's visual, vestibular, and proprioceptive systems activating while executing a task (Georgiev et al., 2021). The TAP theory predicts that the cognitive processes between performing a skill in VR versus the RW should be very similar, even if the movement kinematics differ, and should thus facilitate positive transfer of motor skill learning. Markwell (2023) provided preliminary support for the TAP theory as it relates to VR, specifically showcasing that IVR produced an environment in which the learner was provided with similar task (i.e., sensory) information as the RW task environment, evidenced by a lack of performance and neural activity differences between the IVR and RW practice groups. Previous studies suggest that when sensory information differs between environments, neural activation and network responses also differ (Alsuradi et al., 2020;

Ehinger et al., 2014; Harris et al., 2019). As a result of there being no differences between neural activation patterns between VR and RW practice, it is possible that practicing a task in a sensory rich VR environment facilitates the same motor learning effects as practicing the same task in the RW. However, additional studies including measures of RW transfer are needed to fully validate the predictions made by the TAP theory.

Behavioral Explanations

Other principles of behavior change provide additional explanations for the utility of VR for motor skill learning. E.L. Thorndike's theory of identical elements proposes that the higher the degree of similarity between two skills or two performance contexts, the more likely it is that positive transfer of learning will occur (Thorndike & Woodworth, 1901). However, the current body of work provides contradictory, albeit minimal, evidence for the applicability of this theory. For example, in one previous study, Hejtmanek and colleagues (2020) created a realistic 3D rendering of a RW environment to investigate spatial knowledge acquisition. In that study, participants learned a campus building environment by physically navigating the RW building, or by navigating the building using an IVR rendering delivered through a HMD while walking on an omnidirectional treadmill, or a third group used a computer mouse and keyboard to navigate a virtual rendering on a desktop. Their results indicated positive transfer from VR to RW spatial navigation, with IVR displaying a slight advantage over the desktop learning environment (Hejtmanek et al., 2020). A recent systematic scoping review bolsters these results, concluding virtual environments presented in HMDs are more similar to the RW (i.e., have more identical elements) than virtual environments presented via computer screens (Hepperle & Wölfel, 2023). These findings highlight how high-fidelity VR environments, characterized by detailed graphics, accurate physics, and responsive interactions within the VR environment, can be extremely realistic, but fidelity (i.e., how "real" the experience feels) is not the only factor to consider in regard to motor learning. For example, Bufton and colleagues (2014) highlighted how movement kinematics, such as wrist and elbow joint angle and hand path distance and speed, can differ greatly when performing the same task in virtual and RW environments. Although these learners experienced some degree of success in the early stage of learning, adopting unnatural or compensatory movement patterns could lead to poor performance later in learning. Without adequate RW practice to compensate, this could ultimately lead to negative RW transfer of learning. The facilitation of negative transfer of learning is a significant issue for researchers and practitioners to consider. Although Markwell (2023) found no significant differences in performance between RW and VR practice groups across four days of practice, VR research incorporating prolonged skill acquisition periods and assessments of transfer of learning remain limited and therefore require further investigation.

Summary and Future Directions

Since the first HMD was patented in 1960, VR has undergone a remarkable evolution to become a multifaceted tool utilized across a variety of industries. While military interest, workforce development, and the entertainment industry were the driving forces for its advancement throughout much of its early history, the introduction of gaming companies such as Nintendo and Sony in the 1990s helped propel VR to mainstream popularity. Today's VR technology is more powerful, usable, comfortable, and affordable than any of its predecessors.

Over the past decade there has been a substantial increase in VR research across a variety of fields, including computer science, engineering, clinical medicine, rehabilitation, and neuroscience (Cipresso et al., 2018). Based on level of immersion, the VR technology utilized in research can best be classified into three types: immersive, which utilizes HMDs to achieve a full

360° visual experience (Cruz-Neira et al., 1992); non-immersive, which is limited to desktop and screen displays (Radianti et al., 2020); and semi-immersive, which involves multiple large screens or computer monitors for a more involved experience while still maintaining a connection to the RW. These three types of VR can be utilized to facilitate RW transfer of practical skills, increase access to those with limited resources, and enhance the effectiveness of distance learning (Kavanagh et al., 2017). Unlike traditional learning tools that typically focus on just one or two sensory systems, VR allows visual, auditory, and kinesthetic modalities to be used concurrently, helping to facilitate learning across multiple cognitive levels (Adams, 2015; Fowler, 2015). Additionally, VR's increasing ability to mimic RW experiences has sparked heightened interest in its utility not just for cognitive skill development but also as an important tool for motor skill learning.

VR practice has been studied across various motor skills and contexts, including clinical medicine, rehabilitation, military training, and sport. For example, VR technology can facilitate a wide range of practice scenarios that mirror the complexity of real-life patient care. Research has shown that VR training can help surgical residents gain technical skills (Torkington et al., 2001), improve operative outcomes (Seymour et al., 2002), and positively impact self-confidence (Bani Salameh et al., 2024; Pulijala et al., 2018). Overall, VR presents a cost- and time-effective modality of training for medical resident educators (Cevallos et al., 2022).

In addition to medical and rehabilitation training, the area of clinical neurology has increasingly embraced VR as a research focus (Cipresso et al., 2018). The research conducted in these fields has shown that VR can be an effective tool for improving both cognitive and motor function in stroke patients (Adamovich et al., 2009; Bao et al, 2013; Laver et al., 2017; Wiley et al., 2022). Similarly, individuals with CP who practice with VR have been shown to improve motor performance (Adamovich et al., 2009). Furthermore, patients who utilize VR have reported greater levels of enjoyment (Adamovich et al., 2009) and increased satisfaction with the rehabilitation process (Wiley et al., 2022). For practitioners, VR offers a controlled environment in which training difficulty can be systematically tailored to individual patient needs (Adamovich et al., 2009).

In addition to developing medical and therapeutic practitioners, VR presents a meaningful opportunity to aid in the development of safe and effective military training protocols. For instance, VR technology can be used to simulate real soldier and combat scenarios such as cockpit operations, equipment failures, or adverse weather conditions (Liu et al., 2018). These experiences facilitate greater task-specific problem-solving at a fraction of traditional costs and reduced physical risk to the warfighter (Lele, 2013; Liu et al., 2018). However, due to the significant lack of studies including measures of RW transfer, further evaluation is still necessary (Cross et al., 2023).

The current body of VR literature as it pertains to sport is not as robust as empirical clinical domains, but the limited research which does exist shows promising results for the effectiveness of VR training. Research including measures of RW transfer suggest that VR training can effectively transfer motor skills to RW performance in sports such as rowing (Rauter et al., 2013), dart-throwing (Tirp et al., 2015), baseball (Gray, 2017), table-tennis (Michalski et al., 2019b), and golf putting (Markwell et al., 2023). One potential benefit of training in VR is its ability to easily incorporate practice variability, an important component of training both closed and open motor skills. Research has shown positive transfer from VR practice to RW performance in both closed skills (Markwell et al., 2023; Tirp et al., 2015) and open skills (Gray, 2017; Michalski et al., 2019b; Rauter et al., 2013). However, despite evidence that VR may improve decision-making and response preparation when performing open skills (Streuber et al., 2012), VR training for skills that are inherently unpredictable (i.e., open) remains underexplored. This highlights the need for further research involving motor skills with varying characteristics and classifications, specifically more research investigating open skills that require the performer to adapt their movements based on changing conditions. One example of this would be simulating live game play for a basketball player rather than just isolated skills like a free throw.

Theoretical explanations for the effectiveness of VR training can best be separated into neural, psychological, cognitive, and behavioral lines of investigation. Using fMRI, EEG, and other neuroimaging techniques, research into the neural basis for transfer of learning from VR to the RW highlights that both IVR and NIVR interventions are capable of inducing brain activation patterns and neuroplastic changes similar to those observed during RW task practice (Bao et al, 2013; Izzetoglu et al., 2021; Keller et al., 2020; Kelly & Garavan, 2005; Kober et al., 2021; Markwell, 2023). However, some research reports differences in brain activation patterns between VR and RW conditions (Fernández et al., 2017; Pacheco et al., 2017), indicating the need for further investigation to better understand how practicing a task in a virtual environment neurologically compares to practicing the same task in the RW.

In addition to investigating neuromechanical mechanisms, research on the psychological impact of VR training suggests that it can enhance factors such as engagement (Allcoat & von Mühlenen, 2018), enjoyment (Adamovich et al., 2009; Markwell et al., 2023; Wiley et al., 2022), and intrinsic motivation (Markwell et al., 2023). While IVR has been found to elevate levels of engagement and other positive emotions (Allcoat & von Mühlenen, 2018), results across studies are not always consistent. For instance, in a recent study by Markwell and colleagues (2023), there were no significant differences in engagement across conditions. However, enjoyment is consistently reported higher following VR interventions (Adamovich et al., 2009; Markwell et al., 2023; Wiley et al., 2022).

Beyond affective mechanisms, research investigating the aspects of VR practice related to cognitions suggest that high interactivity in VR experiences can elicit similar cognitive processes to those used when performing the RW task (Georgiev et al., 2021). According to the TAP theory (Morris et al., 1977), this similarity should facilitate positive transfer of learning even if the movement kinematics differ, but further research is needed to test this theory fully. From a behavioral perspective, Thorndike's theory of identical elements predicts that the greater the degree of similarity between the movements required to perform the skills in the VR and RW environments, the more positive transfer of learning will be observed (Thorndike & Woodworth, 1901). While research investigating spatial navigation provides some support for this theory (Hejtmanek et al., 2020), Bufton and colleagues (2014) highlighted how movement kinematics can differ greatly between VR and RW environments, which may facilitate negative transfer of learning effects. Although greater similarity is beneficial for task transfer (Thorndike & Woodworth, 1901), some variability in task performance may not result in negative transfer of learning to RW performance outcomes (Bufton et al., 2014). However, it is unclear what the magnitude of similarity must be to facilitate positive transfer (Abernethy, 1993; Bufton et al., 2014), so additional research on this topic is still needed.

Altogether, one of the biggest issues plaguing the current body of VR research is the inconsistency in defining VR. More specifically, there is presently a lack of distinction between IVR and NIVR technologies in the existing literature. Both conditions have demonstrated positive transfer to RW tasks independently (Adamovich et al., 2009; Bao et al, 2013; Gray, 2017; Michalski et al., 2019b; Rauter et al., 2013; Tirp et al., 2015; Torkington et al., 2001), but research comparing the two forms of VR to one another is limited. Of these studies, some have reported positive benefits of NIVR, such as better practice performance and more positive transfer between simulated experiences (Frederikson et al., 2020; Juliano & Liew, 2020), while one study demonstrated positive effects of IVR practice, such as increased satisfaction and feelings of flow (Polechoński et al., 2024). This highlights a critical need for further research directly comparing IVR and NIVR environments. Therefore, comprehensive study designs including behavioral, psychological, and physiological measurements are crucial to discerning the distinct impact of IVR and NIVR technology on RW performance application. Directly investigating the comparison of IVR and NIVR to one another will advance our theoretical and practical understanding regarding the methods which should be used to optimize human performance and learning through the adoption of VR technology.

CHAPTER I: EXPERIMENT ONE: COMPARING BEHAVIORAL, PHYSIOLOGICAL, AND PSYCHOLOGICAL RESPONSES TO THE SAME STATIONARY CYCLING TASK IN IMMERSIVE VERSUS NON-IMMERSIVE VIRTUAL ENVIRONMENTS

Abstract

Rapid advancements in virtual reality (VR) technology, and the emergence of low-cost VR headsets, have stimulated increased interest from both users and researchers. While both immersive virtual reality (IVR) and non-immersive virtual reality (NIVR) environments have demonstrated positive transfer to real-world (RW) tasks, few studies in the existing literature have directly compared these environments. Preliminary research findings have been mixed and highlight several limitations still needing to be addressed. Therefore, the primary purpose of the present study was to investigate the effects of virtual reality immersion on motor behavioral, physiological, and psychological factors by having participants complete the same stationary cycling task in both NIVR and IVR conditions. Twenty-nine participants were included in the final analysis. Participants performed two 8000-meter trials on two separate days within a one-week time frame, separated by at least seventy-two hours. NIVR trials were completed utilizing a three-dimensional, wall-projected environment while IVR trials were completed using the Meta Quest 2. Course completion time (s), success rate, heart rate (bpm), speed (kph), cadence (RPM), and power output (W) were collected for each trial. Participants also completed the Intrinsic Motivation Inventory (IMI) and Engagement Scale Questionnaire (ESQ) as well as reported their rated perceived exertion (RPE) following each trial. Analyses revealed a significantly greater success rate, higher reported RPE, and greater intrinsic motivation in the IVR condition compared to the NIVR condition, but no significant differences in completion time, heart rate, speed, cadence, power output, or engagement were found between conditions. These results provide valuable insights for making informed decisions about VR training and development with respect to achieving specific outcome goals.

Introduction

Rapid advancements in virtual reality (VR) technology, and the emergence of low-cost options such as the Oculus and HTC Vive headsets, have stimulated increased interest from users and researchers alike (Cipresso et al., 2018). While increasingly used for gaming and entertainment, VR technologies have become a training tool for fields ranging from education (Allcoat & von Mühlenen, 2018; Fowler, 2015; Kavanagh et al., 2017) to clinical medicine and rehabilitation (Adamovich et al., 2009; Cevallos et al., 2022; Cipresso et al., 2018) to sport (Michalski et al., 2019a). However, this growing area of research has been complicated by the inconsistency in defining "virtual reality." Most research utilizes VR as a broadly defined generic term to describe synthetic environments which are created using technology. For the purpose of the proposed study, it is important to distinguish between immersive virtual reality (IVR) and non-immersive virtual reality (NIVR) technologies. By utilizing a full 360° visual experience, IVR technologies change the user's perspective with their head movements, maintaining complete visual immersion in the virtual environment (Cruz-Neira et al., 1992). By comparison, NIVR technologies have a less than 360° visual experience and involve two-dimensional (2D) or three-dimensional (3D) technology that do not maintain the virtual environment with the movement of the user (Adamovich et al., 2009). While both forms of VR have demonstrated positive transfer to real-world (RW) tasks independently (Adamovich et al., 2009; Bao et al, 2013; Gray, 2017; Michalski et al., 2019b; Rauter et al., 2013; Tirp et al., 2015; Torkington et al., 2001), few studies have directly compared IVR and NIVR environments. Those that have, have focused primarily on clinical assessments (Kiper et al., 2020; Plechatá et al., 2019; Ventura et al., 2019) rather than improvements in motor performance, which have demonstrated mixed results (Frederikson et al., 2020; Juliano & Liew, 2020; Polechoński et al., 2024).

As an example of the mixed findings reported in previous research, Juliano and Liew (2020) investigated the transfer of learning effects between a head-mounted display (HMD) VR training condition (i.e., IVR) and a console-based computer screen training condition (i.e., NIVR). Seventy participants completed a modified version of the Sequential Visual Isometric Pinch Task (SVIPT) in either a HMD-VR environment or a computer screen environment. Participants were seated in the same location and used the same transducer across conditions, with the only difference between conditions being the use of the HMD. Researchers evaluated participants' assigned condition performance as well as their performance in the opposite practice condition (i.e., transfer of learning), simulator sickness, and perceptions of presence. While there were no differences in motor skill acquisition, simulator sickness, or perceptions of presence between the two groups, participants assigned to the computer screen environment demonstrated positive transfer to the HMD environment, while participants in the HMD environment demonstrated negative transfer to the computer screen. In other words, practicing in the NIVR condition improved performance in the IVR environment, whereas practicing in the IVR condition negatively impacted performance in the NIVR environment. While it is important to understand motor skill transfer from virtual environments, this study did not include a retention interval, which is typical of experimental designs intended to test motor skill transfer (Juliano & Liew, 2020). Additionally, while the rationale for the study was grounded in rehabilitation, researchers only evaluated transfer between simulations and did not measure real-world (RW) transfer. These limitations highlight the need for additional research comparing training outcomes between NIVR and IVR training environments.

Like Juliano and Liew (2020), Frederikson and colleagues (2020) utilized a HMD to create an immersive training condition and a computer screen to create a non-immersive training condition. Thirty-one first-year residents were randomly assigned to either the IVR experimental condition or NIVR control condition to practice a laparoscopic salpingectomy procedure. During practice in the IVR condition, four phases of environmental stress were employed as backdrops during the procedure: two calm situations in which staff quietly rearranged instruments around the procedure "room," one light stressor in which the anesthesiologist can be heard having a conversation and the floor nurse answering a ringing phone, and one severe stressor where bleeding occurs in the procedure and several nurses react to it. Participants in the NIVR condition practiced only in the calm environment. Cognitive load was assessed via secondary reaction time at four set timepoints during the simulations, overall performance data, and motion sickness were also evaluated. Participants demonstrated significantly better practice performance in the NIVR condition compared to the IVR condition. However, participants in the IVR group experienced significantly greater cognitive load, which researchers noted as being more reflective of real-life conditions (Frederikson et al., 2020). A key limitation of this study is that the IVR and NIVR conditions did not utilize the same four stressor phases, which limits the validity of direct comparisons between the two experimental conditions. These findings highlight the need for further research to better understand how IVR and NIVR training environments may be utilized to achieve different outcome goals.

Most recently, Polechoński and colleagues (2024) compared levels of satisfaction and flow, defined as an optimal mental state characterized by full engagement with the activity being performed, across real life (RL), NIVR, and IVR cycling conditions on a stationary bicycle. Prior to testing, participants (*n* = 40) completed the Physical Activity Enjoyment Scale (PACES) and Flow State Scale (FSS) concerning riding a standard bicycle in natural conditions and a stationary bicycle without any visualizations. They completed these questionnaires again after each of two stationary bicycle activity sessions. In "session 1", participants completed a stationary bicycle course in an NIVR condition, and "session 2" in a matched IVR condition. While participants reported significantly higher satisfaction and feelings of flow in the IVR condition, there are several limitations to consider before the findings of this study can be fully understood. For example, performance metrics were not collected, so results were based solely on self-report measures following the completion of the testing. Additionally, participants completed questionnaires concerning RL conditions prior to any activity participation, unlike the VR conditions, where questionnaires were completed following a training session. Furthermore, although the simulations were nearly identical, the use of handlebars as a grounding element in the NIVR condition can function similarly to an avatar by providing the user with a visual/physical reference point in the virtual environment, which may shift the user's perspective from first-person to third-person. This shift in perspective could potentially limit direct comparisons between the virtual experimental conditions. While this study offers initial insights into how VR may influence affective responses, conclusions regarding motor performance and learning remain unclear. Therefore, further research is needed to address these gaps and limitations.

Considering the gaps and limitations outlined above, the primary purpose of this study was to investigate the effects of virtual reality immersion on motor behavioral (e.g., completion time, success rate, cadence, speed, & power), physiological (e.g., heart rate), and psychological (e.g., rated perceived exertion [RPE], intrinsic motivation, & engagement) factors by having participants complete the same stationary cycling task in both a non-immersive and immersive virtual reality environment. To address limitations in the existing literature and facilitate direct comparisons, the NIVR and IVR simulations were designed to be identical, maintaining a first-person perspective in both conditions. Building upon the findings reported by Juliano and Liew (2020) and given that the task remained consistent across conditions in the current study, it was hypothesized that there would be no significant differences in motor behavioral measures between conditions (e.g., completion time, success rate, cadence, speed, & power). However, because IVR has been shown to elicit greater affective responses (Frederikson et al., 2020; Polechoński et al., 2024), it was hypothesized that there would be significant differences in psychological measurements (e.g., rated perceived exertion [RPE], intrinsic motivation, & engagement), specifically that participants would report greater RPE, intrinsic motivation, and engagement in the IVR condition. Lastly, aligning with previous studies demonstrating that IVR increases sympathetic nervous system activity (Malińska et al., 2015), it was hypothesized that there would be significant differences in physiological measurements (e.g., heart rate), specifically that heart rate would be higher in the IVR condition. If these predictions are correct, it would suggest that while VR immersion may not significantly impact motor behavioral outcomes, it does impact psychological and physiological factors within the performer. These findings would help researchers, practitioners, and developers make informed decisions about utilizing VR training and development to achieve specific outcome goals.

Method

Participants

A total of 35 university students participated in the present study. Six participants were excluded from analyses as a result of incomplete data due to technology error or partial study completion. Of the remaining 29 participants included in the analyses, 22 were female and seven were male, ranging in age from 18-27 (M_{age} = 21.00, SD_{age} = 2.45). Participants were excluded for scores exceeding 25 on the Motion Sickness Susceptibility Questionnaire short-form (MSSQ-short) or if they answered “yes” to any of the questions on the Physical Activity Readiness Questionnaire (PAR-Q). Additionally, participants were excluded from the study if their heart rate exceeded the maximum safe cutoff during participation, which was predetermined by subtracting their age from 220. An *a priori* power analysis was performed using G*Power statistical power analysis software version 3.1.9.6 to determine the minimum required sample size. The analysis was based on a within factors repeated measures analysis of variance (ANOVA), assuming a medium effect size ($f = 0.50$), an alpha level of 0.05, and desired power of 0.80. The analysis yielded a recommended minimum sample size of 28 participants.

Task and Apparatus

All data collection for this experiment took place in a climate-controlled research laboratory. A WahooKICKR indoor stationary bicycle (Wahoo Fitness, Georgia, United States) was used in both conditions. All participants underwent a standardized procedure to determine proper bike fit. Measured manually using a handheld metal goniometer, the saddle height was adjusted so that the participant’s knee flexion angle was approximately 25-30° with the pedal at the dead bottom position (180°) (Bini et al., 2011; Hummer et al., 2021). Using a plum bob with the pedal at the dead bottom position, the saddle fore-aft position was set to align the patella with the pedal spindle (Fang et al., 2016; Gardner et al., 2015; Hummer et al., 2021). The handlebar position was adjusted so that the participant’s trunk angle was 90° with the axis at the iliac crest (Fang et al., 2016; Hummer et al., 2021).

The MSSQ-Short and PAR-Q questionnaires were used to determine participant eligibility. The MSSQ-Short (Appendix A) was used to determine participant susceptibility to motion sickness, defined by feelings of queasiness, nausea, or actual vomiting. Participants were asked to indicate how often they felt sick or nauseated on a numerical rating scale of 0-3 anchored by “never felt sick” and “frequently felt sick.” Participants were excluded for scores exceeding twenty-five on the MSSQ-Short. The PAR-Q (Appendix B) was used to screen participants for evidence of risk factors and recent injuries. If a participant answered “yes” to any of the general screening questions, which would indicate a medical risk factor or recent injury, they were excluded from participation.

Participants performed two 8000-meter trials on two separate days within a one-week time frame, separated by at least 72 hours. The non-immersive virtual reality (NIVR) trial was completed utilizing a three-dimensional, wall-projected environment projected from a tablet running on Android OS via an Epson PowerLite 1780W (Epson America, Inc., California, United States) projector (see Figure 12). The Wahoo bike was positioned 295.15 cm away from the wall projection. The immersive virtual reality (IVR) trial was completed using the Meta Quest 2 virtual reality headset (see Figure 13). The order in which the conditions were completed was counterbalanced across participants. Participants were informed the course was set to a fixed distance and that researchers would measure the number of tokens collected and time to completion. Participants were not made aware of the other dependent measures being collected.

Both virtual reality conditions were custom designed using the cross-platform game engine Unity 3D (Version 2022.3.16). The applications were designed to give the user consistent experiences across immersive and non-immersive platforms. The cycling scene features a low-poly virtual environment designed to appear endless to the user. The user remains fixed in one of three lanes but can switch lanes using the corresponding handlebar buttons on the Wahoo bike. Pedaling resulted in the optical perception that the user was moving forward, with the application progressing at a speed that matches the user’s pedaling rate. Tokens were scattered across the cycling lanes, and users collected points by pedaling through each token. The user’s perspective was consistent across applications, maintaining a first-person viewpoint in the NIVR condition without the use of grounding elements such as an avatar or handlebars. All participants were physically seated in the same position on the same indoor stationary bicycle for both days of participation. The only difference between the NIVR and IVR conditions was the use of the HMD in the IVR condition, which altered participants' field of view of the cycling scene. Refer to Figures 12 and 13 below for photographic representation of the NIVR (Figure 12) and IVR (Figure 13) experimental setup and animation representation.

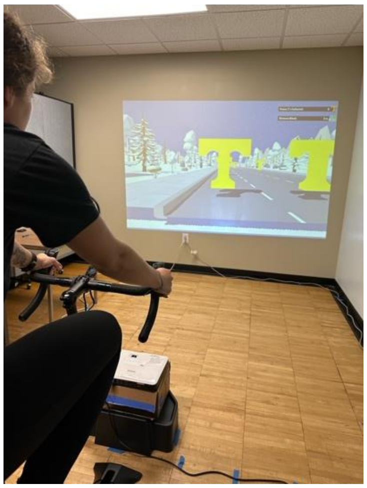

Figure 12. Experiment One: NIVR condition.

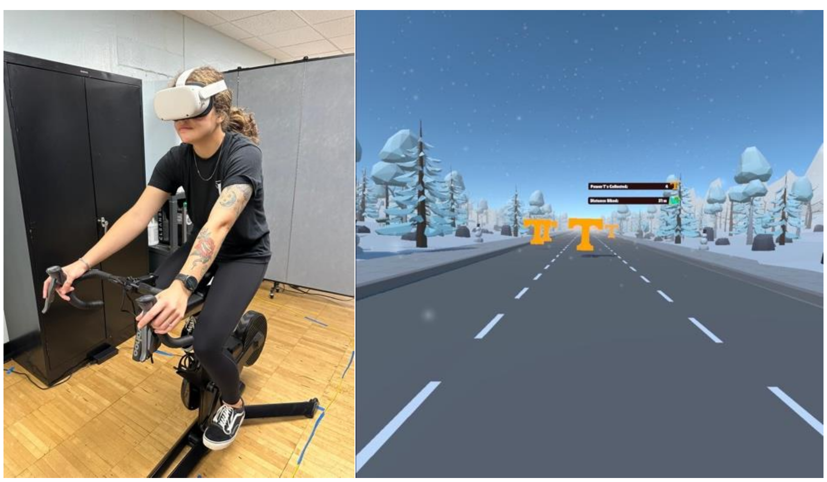

Figure 13. Experiment One: IVR condition. The image on the right side of the panel provides an example of the animation the participant observed inside the IVR headset.

Motor Behavioral Measurements

Course completion time was recorded in seconds (s) via the cycling course application. Success rate was calculated by dividing the number of tokens collected by the total number of tokens which were made available to the participants. Token location across the three lanes was randomized, and tokens were generated at a rate proportional to participants' movement speed, resulting in an approximately consistent number of tokens per meter traveled.

Participants' speed was recorded in kilometers per hour (kph), cadence in revolutions per minute (RPM), and power output in watts (W) via the WahooKICKR.

Physiological Measurements

Average heart rate was recorded in beats per minute (bpm) via the WahooKICKR.

Psychological Measurements

Participants' experiences were measured via the Intrinsic Motivation Inventory (IMI) and Engagement Scale Questionnaire (ESQ). The IMI (Appendix C) contains statements related to six subscales: interest/enjoyment, perceived competence, effort, value/usefulness, pressure/tension, and perceived choice. Participants were asked to indicate how true each statement was on a numerical rating scale of 1-7 anchored by "not at all true" and "very true." The ESQ (Appendix D) contains statements related to three subscales: behavioral engagement, cognitive engagement, and emotional engagement. Participants were asked to indicate the extent to which they agreed with each statement on a numerical rating scale of 1-5 anchored by "strongly disagree" and "strongly agree." Participants were asked to verbally indicate their RPE immediately following completion of the task on a rating scale of 1-10 anchored by "hardly any exertion" to "it feels almost impossible to keep going."

Procedure

Approval from the University's Institutional Review Board (IRB-22-06810-XP) was obtained prior to participant recruitment. Participants were recruited from the college's Department of Kinesiology, Recreation, and Sport Studies. After providing informed consent, participants completed the MSSQ-short and PAR-Q questionaries. Participants were excluded for scores exceeding 25 on the MSSQ-short or if they answered "yes" to any of the questions on the PAR-Q. Next, participants' maximum safe heart rate cutoff was determined by subtracting their age from 220. If participants' heart rate exceeded this number at any point during either session, their participation was stopped. The bike was then fitted to the participants' unique measurements and participants were equipped with a heart rate monitor strapped around the chest following manufacturer fitting guidelines.

This study utilized a within-subjects experimental design. The order in which participants completed the experimental conditions (i.e., NIVR or IVR) was counterbalanced. After the bike and heart monitor were fitted to the participant, they completed a pre-test IMI. The researcher then verbally read standardized instructions for the cycling task to the participant (Appendix E). Participants were informed that researchers would record the number of tokens collected and time to completion but were blind to the other performance variables being collected. Each participant was told that the scene in the application would move at the same speed as their pedaling rate. The researcher also explained how to switch lanes within the application using the buttons on the bike. After the initial instructions were provided and surveys completed, participants then completed the task in either the NIVR or IVR condition. Following task completion, participants completed the IMI and ESQ in a counterbalanced order.

Following the first day of participation, participants returned at least forty-eight hours but no more than one week later to complete the second day of participation. Participants followed the same procedure on day two for the remaining experimental condition (i.e., NIVR or IVR). Following completion the second day of testing, participants were verbally asked, “Having completed both conditions, which did you prefer?” Participants then returned all equipment and were thanked for their participation.

Data Analysis

All data collected in this study were analyzed using IBM SPSS Statistics version 29.0.2.0. Twelve separate paired-samples *t*-tests were used to assess completion time, success rate, RPE, and engagement, as well as both averages and maximums for measures of heart rate, speed, cadence, and power. Given the sample size (<30), normality tests were conducted. While some measures deviated from a normal distribution, Wilcoxon Signed Rank Tests produced similar results. Therefore, the results of the paired-samples *t*-test are reported below. Separate 2 (pre/post) x 2 (condition) repeated measures ANOVAs were used to assess global intrinsic motivation scores and each of the six IMI subscales (interest/enjoyment, perceived competence, effort/importance, pressure/tension, perceived choice, & value/usefulness).

Results

Motor Behavioral Measurements

Separate paired-samples *t*-tests were used to assess completion time and success rate, and to assess both averages and maximums for measures of speed, cadence, and power (See Table 1). The analysis revealed a significant main effect of condition, $t(28) = -3.25$, $p = .003$, $d = -.60$, with the IVR condition showing higher success rates than the NIVR condition. There were no significant differences between conditions for completion time, $t(28) = .42$, $p = .68$.

Table 1. Means and standard deviations for motor behavioral measurements. The * in the above table indicates a significant difference for the Success Rate measure.

Measure	NIVR Mean (SD)	IVR Mean (SD)
Completion Time (s)	1686.12 (284.34)	1668.44 (243.10)
*Success Rate (%)	51.66 (4.02)	54.14 (3.81)
Average Speed (kph)	19.22 (9.88)	19.41 (10.07)
Maximum Speed (kph)	23.14 (12.01)	22.47 (11.54)
Average Cadence (rpm)	85.79 (14.11)	85.75 (12.97)
Maximum Cadence (rpm)	108.41 (20.85)	106.70 (20.36)
Average Power (W)	82.48 (22.10)	82.64 (22.39)
Maximum Power (W)	218.89 (142.34)	201.04 (113.76)

Physiological Measurements

Separate paired-samples *t*-tests were used to assess both average and maximum heart rate. The analysis revealed no significant differences between conditions (See Tables 2 and 3).

Table 2. Means and standard deviations for physiological measurements.

Measure	NIVR Mean (SD)	IVR Mean (SD)
Average Heart Rate (bpm)	138.72 (23.29)	138.68 (18.88)
Maximum Heart Rate (bpm)	162.15 (29.21)	157.12 (19.69)

Table 3. Paired-samples t-tests results for behavioral and physiological measurements.

Measure	*t(df)*	p-value
Average Speed	-.39(26)	.70
Maximum Speed	1.12(26)	.25
Average Cadence	.02(26)	.98
Maximum Cadence	.60(26)	.56
Average Power	-.06(26)	.95
Maximum Power	1.22(26)	.23
Average Heart Rate	.01(25)	.99
Maximum Heart Rate	1.02(25)	.32

Psychological Measurements

Separate paired-samples *t*-tests were used to assess RPE and engagement (See Table 4). The analysis revealed a significant main effect of condition for RPE, $t(28) = -2.34$, $p = .027$, $d =$ -

.42, with higher RPE reported in the IVR condition compared to the NIVR condition. There were no significant differences between conditions for engagement, $t(27) = -.43$, $p = .67$.

Table 4. Means and standard deviations for psychological measurements. The * in the above table indicates a significant difference for global IMI and the Interest/Enjoyment and Value/Usefulness IMI subscales.

Table 4. Means and standard deviations for psychological measurements. The * in the above table indicates a significant difference for global IMI and the Interest/Enjoyment and Value/Usefulness IMI subscales.

Measure	NIVR Mean (SD)	IVR Mean (SD)
RPE	5.28 (1.91)	5.86 (1.88)
Engagement	4.49 (0.74)	4.23 (0.59)
Pre-test IMI	4.69 (0.48)	4.73 (0.44)
*Post-test IMI	4.85 (0.62)	4.92 (0.59)
Pre-test IMI - Interest/Enjoyment	3.91 (1.12)	4.15 (1.09)
*Post-test IMI - Interest/Enjoyment	4.58 (1.27)	4.69 (1.19)
Pre-test IMI - Perceived Competence	4.49 (1.01)	4.54 (1.06)
Post-test IMI - Perceived Competence	4.58 (1.15)	4.69 (1.16)
Pre-test IMI - Effort/Importance	5.45 (0.78)	5.48 (0.77)
Post-test IMI - Effort/Importance	5.48 (0.95)	5.60 (0.90)
Pre-test IMI - Pressure/Tension	2.44 (0.91)	2.22 (0.90)
Post-test IMI - Pressure/Tension	2.09 (0.70)	2.21 (0.88)
Pre-test IMI - Perceived Choice	6.51 (0.59)	6.44 (0.64)
Post-test IMI - Perceived Choice	6.50 (0.60)	6.39 (0.60)
Pre-test IMI - Value/Usefulness	4.91 (1.12)	5.00 (1.00)
*Post-test IMI - Value/Usefulness	5.22 (1.21)	5.30 (1.02)

Separate 2 (pre/post) x 2 (condition) repeated measures ANOVAs were used to assess global intrinsic motivation scores and each of the six IMI subscales (See Table 4). The analysis revealed a significant main effect for condition for global intrinsic motivation $F(1, 27) = 5.78$, $p = .02$, $\eta^2 = .18$, with participants reporting higher global intrinsic motivation in the IVR condition. However, there was no main effect for time (i.e., pre/post) $F(1, 27) = 0.76$, $p = .39$, $\eta^2 = .03$, and no interaction effect between time and condition $F(1, 27) = 0.11$, $p = .74$, $\eta^2 = .004$.

Additionally, the analyses for each of the six subscales revealed a significant main effect for condition on the interest/enjoyment and value/usefulness subscales, with participants reporting higher values in the IVR condition than NIVR condition. There were no significant differences between conditions for perceived competence, effort/importance, pressure/tension, and perceived choice subscales (see Table 5).

Table 5. Repeated measures ANOVA results for the six IMI subscales.

IMI Subscale	df	F	p-value	partial η^2
Interest/Enjoyment	(1, 27)	9.76	.004*	.27
Perceived Competence	(1, 27)	1.49	.23	.05
Effort/Importance	(1, 27)	.29	.60	.29
Pressure/Tension	(1, 27)	2.44	.13	.08
Perceived Choice	(1, 27)	.33	.57	.01
Value/Usefulness	(1, 27)	9.59	.005*	.26

*$p < .05$

Experiment 1 Discussion

The present study investigated the effects of virtual reality immersion on motor behavioral (e.g., completion time, success rate, cadence, speed, & power), physiological (e.g., heart rate,), and psychological (e.g., RPE, intrinsic motivation, & engagement) factors by having participants complete the same stationary cycling task in both a non-immersive and immersive virtual reality environment. It was hypothesized that there would be no significant differences in motor behavioral measures between conditions, but that there would be significant differences in physiological measurements and psychological measurements, specifically that these measures would be greater in the IVR condition compared to the NIVR condition. The results of this study partially supported these hypotheses. A more detailed explanation of the results of the experiment will be provided in the following sections.

Motor Behavioral Measurements

Based on previous findings by Juliano and Liew (2020), and given that the task remained consistent across conditions, it was hypothesized that there would be no significant differences in motor behavioral measures between conditions (e.g., completion time, success rate, speed, cadence, & power). These predictions were partially supported. Specifically, the analysis revealed a significantly greater success rate in the IVR condition compared to the NIVR condition, but no significant differences in completion time between conditions. These results are both congruent and contrasting with previous research by Juliano and Liew (2020). The lack of difference in completion time, speed, cadence, and power between conditions can likely be explained by differences in task design used in the present experiment and the methods used by Juliano and Liew (2020). In the present study, the applications were designed to give the user consistent experiences across immersive and non-immersive platforms. Furthermore, the task instructions were standardized across conditions. Therefore, it is not surprising that these metrics did not significantly differ between the two conditions. An additional explanation for these findings could be the enhanced task environment and game-like design. Lohse et al. (2016) observed that practicing a motor skill in a gamified environment improved participant speed and accuracy compared to the same skills in a sterile environment. Both conditions in the present study utilized the same game-like task which may explain why minimal differences were observed between the two groups across all dependent measures. Lohse et al. (2016) further suggested that the performance differences between the gamified and sterile groups could be due to increased engagement in the game environment. However, no significant differences in measures of engagement were found between conditions in the present study, providing further support that the two virtual environments did not result in different amounts of engagement between the two conditions. Additional research is needed to more fully understand how the gamification and immersion level of the VR environment elicits mover engagement and ultimately manifests in changes in motor, physiological and psychological behaviors.

Despite these factors, there were significant differences in success rate, defined as the ratio of collected tokens divided be the total number of tokens available. These findings can most likely be explained by technological limitations in the non-immersive condition. The tablet running on Android OS and the Epson projector were connected via a wireless internet connection, which occasionally resulted in lag or skipped frames due to network instability. These interruptions may have briefly impacted the consistency of visual feedback available to the participant during the task. However, given the moderately large effect size, it is unclear if this is the primary explanation for the observed results. If these findings are not a product of technological limitations, Streuber and colleagues (2012) may provide evidence for an alternative explanation.

In their 2012 study, Streuber and colleagues (2012) asked participants to hit a virtual tennis ball served to them by a virtual player in an IVR environment. Participants demonstrated more accurate strokes when the tennis ball was visible compared to obscured, despite no changes in stroke speed variability of the tennis racket (Streuber et al., 2012). These findings suggest that continuous availability of visual information in VR enhances perception-action coupling, the coupling of specific visual information (e.g., the tennis ball) and motor responses (e.g., the user's stroke). In the present study, tokens were scattered across three cycling lanes, and users collected points by pedaling through each token. Pedaling resulted in the optical perception that the user was moving forward and tokens appeared progressively larger the closer they were to the participant (See Figures 12 and 13). Results indicated that participants demonstrated a significantly greater success rate (i.e., collected a higher percentage of tokens) in the IVR condition compared to the NIVR condition, but showed no significant differences in speed between conditions. Without the use of a grounding element (e.g., avatar, arrow, etc.) in the NIVR condition to help anchor the perception of the user in the virtual scene, it is possible the distance between the bike and the projected screen (295.15 cm) acted as a type of perceptual impedance or environmental constraint which limited visual perception. Although vision was not occluded in the NIVR condition, the lack of a grounding element coupled with the physical distance between the participant and the screen may have reduced participants' sense of spatial connection to the virtual environment, weakening visual-motor response coupling. While this lack of grounding element was an intentional choice for the purpose of the present study, the findings of a recent experiment suggest grounding is more important in the facilitation of an interactive user experience in VR relative to embodiments (i.e., ability to change perspective) (Lachmair et al., 2022). Therefore, the absence of this occlusion and resulting greater sense of grounding in the IVR environment may have facilitated stronger perception-action coupling compared to the NIVR environment, contributing to the higher success rate observed in the IVR condition. However, it should be noted that the current body of research on this topic is limited, and further exploration is needed to address these limitations and discern a clear explanation.

Physiological Measurements

Findings by Malińska and colleagues (2015) suggest that IVR training environments result in increases in sympathetic nervous system activity. Therefore, it was hypothesized that the IVR condition would result in greater physiological responses. The results of the current study did not support this hypothesis, as there were no significant differences between conditions on average or maximum measures of heart rate. While these results are somewhat surprising given previous research (Malińska et al., 2015), the behavioral results of the present study provide further support for these findings. Specifically, there were no significant differences between conditions in completion time, speed, cadence, or power, it is unsurprising that heart rate also did not significantly differ.

Psychological Measurements

Based on previous findings by Frederikson et al. (2020) and Polechoński et al. (2024), it was hypothesized that participants would report greater RPE, intrinsic motivation, and engagement in the IVR condition relative to the NIVR condition. These predictions were partially supported. The analyses revealed a significant main effect of condition for measures of RPE and intrinsic motivation, but no significant differences in measures of engagement. These results align with recent findings from Markwell and colleagues (2023), who compared IVR and traditional training for a golf-putting task. In Markwell et al.'s (2023) study, participants reported significantly greater intrinsic motivation, but there were no differences between groups in measures of engagement. Interestingly, when Markwell et al. (2023) analyzed the subscales of the IMI, they found only the Interest/Enjoyment subscale to differ significantly between groups. Similarly, when we analyzed the subscales of the IMI, there was a significant main effect for condition on the Interest/Enjoyment subscale, but also on the Value/Usefulness subscale. Specifically, participants reported higher values in these categories following the IVR condition compared to the NIVR condition These findings suggest that IVR may enhance intrinsic motivation by increasing performer interest/enjoyment as well as their perceived value of the task compared to NIVR. These findings are especially important given intrinsic motivation has been suggested as a contributing factor to motor performance and learning (Wulf & Lewthwaite, 2016).

Summary and Future Directions

The present study sought to determine how virtual reality immersion affected motor behavioral (e.g., completion time, success rate, cadence, speed, & power), physiological (e.g., heart rate), and psychological (e.g., RPE, intrinsic motivation, & engagement) factors by having participants complete the same stationary cycling task in both a non-immersive and immersive virtual reality environment. Consistent with previous research, there was no significant difference in completion time between conditions (Juliano & Liew, 2020). Also consistent with previous research, participants reported significantly greater intrinsic motivation and RPE in the immersive condition compared to the non-immersive condition but did not report significant differences in engagement (Frederikson et al., 2020; Markwell et al., 2023). In addition to these findings, there were several results of the present study that contradicted previous research. Although there was no significant difference in completion time between conditions, the immersive condition resulted in significantly greater success rate compared to the non-immersive condition. Additionally, while previous findings suggest immersive training environments can increase sympathetic nervous system activity (Malińska et al., 2015), the present study did not find significant differences between conditions in any of the physiological measures collected.

The present study addressed a key limitation in the existing literature by creating and implementing identical, first-person perspective virtual reality practice conditions, enabling direct comparisons between the non-immersive and immersive simulations tested. However, findings from the present study should be interpreted with consideration of some limitations. As mentioned above, the non-immersive condition occasionally experienced lagged or skipped frames due to wireless network instability, which may have briefly impacted participants' visual perception. Future studies should address this technological limitation to further explore the relationship between virtual reality immersion and motor behavioral outcomes. Another limitation of the present study is that participants experienced each condition only once. While Keller and Suzuki (2004) suggest that motivational benefits of new media may be driven by a novelty effect that diminishes with repeated exposure, Jeno and colleagues (2019) challenged this idea and highlighted the difficulty of defining and operationalizing novelty. Therefore, future research should incorporate multiple test sessions to better understand this effect in virtual reality settings.

In conclusion, the present study offers a unique contribution to the existing body of research on the motor behavioral, physiological, and psychological outcomes associated with practicing in virtual reality. Moreover, the present study extends previous research (e.g., Frederikson et al., 2020; Juliano & Liew, 2020; Polechoński et al., 2024), by experimentally testing non-immersive and immersive virtual reality environments. Furthermore, the creation and implementation of identical virtual reality simulations across immersive and non-immersive conditions is a key strength of the present study. The results of this study provide researchers, practitioners, and developers with valuable insights for making informed decisions about VR training and development with respect to achieving specific outcome goals.

CHAPTER II: EXPERIMENT TWO: COMPARING BEHAVIORAL, PHYSIOLOGICAL, AND PSYCHOLOGICAL RESPONSES FROM EXTENDED PRACTICE OF THE SAME STATIONARY CYCLING TASK IN IMMERSIVE VERSUS NON-IMMERSIVE VIRTUAL ENVIRONMENTS

Abstract

Virtual reality (VR) technologies, both immersive (IVR) and non-immersive (NIVR) have been accepted as training tools across a variety of fields including education, clinical medicine, and rehabilitation. While IVR training technologies are generally well-received, the current body of literature is limited, and questions remain regarding its effectiveness, advantages, limitations, and feasibility. Therefore, the primary aim of the present study was to expand on previous findings by investigating the effects of virtual reality immersion on motor behavioral, physiological, and psychological factors across multiple practice sessions. Twenty participants were included in the final analyses. Participants performed a total of four 8000-meter stationary cycling trials on four separate days within a two-week time frame. NIVR trials were completed utilizing a three-dimensional, Android tablet application, and IVR trials were completed using the Meta Quest 2. Completion time (s), success rate, heart rate (bpm), speed (kph), cadence (RPM), power output (W), and rated perceived exertion (RPE) were collected at 1000-meter intervals (i.e., laps) during each trial which spanned a total distance of 8000-meters. Participants also completed the Intrinsic Motivation Inventory (IMI) and Engagement Scale Questionnaire (ESQ) following each trial. Analyses revealed there were no significant differences between the first and second day of participation within each condition, and there were no significant differences between conditions for completion time, success rate, and heart rate. There were however significant condition (i.e., NIVR & IVR) X lap interactions for speed, cadence, and power, specifically across laps three through six. No significant differences in RPE, intrinsic motivation, or engagement were found between conditions, but condition order did impact certain IMI subscales. These findings suggest immersion may impact within-task dynamics more

than overall task performance, providing researchers and practitioners with deeper insight into potential pacing behaviors during VR practice.

Introduction

In recent years, virtual reality (VR) has become an increasingly popular technology utilized by researchers and practitioners alike (Cipresso et al., 2018). As of 2022, virtual reality in gaming had an estimated market size of over $20 billion globally and is estimated to grow an additional 22.7% from 2023 to 2030 (Grand View Research, 2023). Although VR has seen an incredible surge in gaming and entertainment, VR technologies have also been accepted as training tools across a variety of fields including education (Allcoat & von Mühlenen, 2018; Fowler, 2015; Kavanagh et al., 2017), clinical medicine and rehabilitation (Adamovich et al., 2009; Cevallos et al., 2022; Cipresso et al., 2018), and sport (Michalski et al., 2019a).

For the purpose of the present study, it is important to distinguish between immersive virtual reality (IVR) and non-immersive virtual reality (NIVR) technologies. IVR technologies utilize a full 360° visual experience to change the user's perspective with their head movements, allowing them to maintain complete visual immersion in the virtual environment (Cruz-Neira et al., 1992). NIVR technologies on the other hand offer less than 360° visual experience and involve two-dimensional (2D) or three-dimensional (3D) technology which does not maintain the virtual environment concurrently with the movement of the user (Adamovich et al., 2009). Both types of VR technology have demonstrated positive transfer to real-world (RW) tasks independently (Adamovich et al., 2009; Bao et al, 2013; Gray, 2017; Michalski et al., 2019b; Rauter et al., 2013; Tirp et al., 2015; Torkington et al., 2001), but few studies have directly compared IVR and NIVR environments for improving motor performance (Frederikson et al., 2020; Juliano & Liew, 2020; Polechoński et al., 2024; Velten, 2024). Additionally, while IVR training technologies are generally well-received in professional skill and safety training contexts (e.g., industrial settings, emergency preparedness, healthcare training, etc.), the current body of literature is still limited and therefore questions remain regarding its effectiveness, advantages, limitations, and feasibility (Renganayagalu et al., 2021).

When comparing an IVR head-mounted display (HMD) to a computer screen training condition (i.e., NIVR), Juliano and Liew (2020) found no differences in motor skill acquisition, simulation sickness frequency, or perceptions of presence between the two groups. The findings reported in the first study of this dissertation (Velten, 2024) both supported and contradicted the findings reported by Juliano and Liew (2020). Specifically, the findings reported in study 1 (Velten, 2024) demonstrated that participants had a significantly greater success rate, a motor behavioral measure specific to the assigned cycling task, but no significant differences in completion time between conditions. While findings from Streuber and colleagues (2012) suggest that this may be attributable to the immersive condition facilitating greater perception-action coupling than the non-immersive condition, Velten (2024) noted that these results were more likely attributable to technological limitations resulting in lag or skipped frames in the NIVR condition resulting in visual perceptive disruptions for the participant.

Contradictory to Juliano and Liew's (2020) findings, when Frederikson and colleagues (2020) utilized immersive and non-immersive VR practice environments to investigate surgical procedure performance, they found participant performance to be significantly better in the NIVR condition relative to the IVR condition. Participants in this experiment also reported significantly higher cognitive load in the IVR condition (Frederikson et al., 2020). However, it is important to note that the two practice conditions did not utilize the same stress inducing protocol and therefore results may be attributed to changes in stress response rather than the immersion level of the two VR simulations. Nevertheless, similar to the findings reported by Frederikson and colleagues' (2020) findings, participants in the first study of this dissertation

(Velten, 2024) reported significantly higher rated perceived exertion (RPE) in the IVR condition compared to the NIVR condition. However, contradicting Frederikson and colleagues' (2020) findings, participants in study 1 (Velten, 2024) demonstrated no significant differences in completion time between conditions. Considering the methodological limitations and contradicting findings of the studies mentioned above (i.e., Frederikson et al., 2020; Juliano & Liew, 2020; Streuber et al., 2012; Velten 2024), it is clear further research is needed to better understand the effect of virtual reality immersion on motor performance. Therefore, the present study sought to further investigate potential performance differences between NIVR and IVR conditions utilizing an Android OS tablet for the NIVR condition, rather than a non-immersive environment projected onto a wall, to address the technological limitations of study 1 (Velten, 2024). Unlike the projection, which relied on a wireless internet connection, the tablet ran on a stored data file, providing a more stable connection to the application. This change in NIVR delivery method ensured visual information to the user was never disrupted, allowing for more accurate perception-action coupling and movement execution within the application. This increased consistency provided by switching to the tablet afforded a more accurate performance assessment and comparison across conditions. Given the goal of the present dissertation is to compare performance between NIVR and IVR environments, assessment consistency and reliability is critical to ensuring any observed differences between conditions can be attributed to immersion rather than the product of technological instability.

In one recent study utilizing a stationary bicycle activity, Polechoński and colleagues (2024) found that participants reported significantly higher satisfaction and feelings of flow in the IVR condition. While that study had notable limitations, including the use of a grounding element in the NIVR condition that may have altered the user's visual perspective, results from study 1 (Velten, 2024) demonstrated similar findings. Specifically, in study 1 (Velten, 2024), participants reported significantly greater RPE and intrinsic motivation in the IVR condition compared to trials completed in the NIVR condition. When the IMI subscales were analyzed, there were significant differences between the conditions on measures of Interest/Enjoyment and Value/Usefulness. Markwell and colleagues (2023), who compared IVR and traditional training (i.e., real-world) environments for a golf-putting task also found the IVR group reported significantly higher intrinsic motivation, particularly in Interest/Enjoyment. However, it is unclear if this increased interest and enjoyment persists with repeated exposure to the immersive environment. Keller and Suzuki (2004) suggest that motivational benefits of new media (i.e., any innovative electronic media designed to make instruction more appealing to learners) may be driven by a novelty effect that diminishes with repeated exposure, but Jeno and colleagues (2019) challenged this idea and highlighted the difficulty of defining and operationalizing novelty. In Markwell and colleagues (2023) study, participants in the immersive virtual reality practice group reported significantly higher intrinsic motivation compared to the real-world practice group following a single day of practice. However, when Markwell (2023, experiment 2) further explored this novelty effect across three days of practice, they found no significant differences in intrinsic motivation between the immersive virtual reality and traditional (i.e., real-world) practice groups. Interestingly, and in contradiction to Keller and Suzuki's (2004) suggestion, Markwell (2023) did find that the virtual reality practice group reported no differences in intrinsic motivation across testing days. In light of Markwell's (2023, experiment 2) findings, and the lack of research comparing this effect based on levels of immersion, the present study sought to expand on research by Jeno and colleagues (2019) and Markwell (2023, experiment 2) by incorporating two test sessions in each condition to further investigate this effect in virtual reality settings. Although research investigating habituation, which is characterized by diminished physiological and psychological responses to a repeated stimulus, in virtual reality is limited, one study found participants to significantly adapt after just four to five repeated sessions of ninety second exposures each (i.e., 6-7.5 minutes in total) (Fransson et al., 2019). These findings suggest that adaptation to virtual environments can occur relatively quickly. On average, participants in study 1 (Velten, 2024) completed each practice session in roughly 28 minutes. Although the practice session was continuous, this duration should be sufficient to enable participant adaptation based on Fransson and colleagues (2019) findings. Therefore, it was hypothesized that one day of practice would act as a habituation trial and a second day of practice would capture effects of diminished novelty, if elicited. From a theoretical perspective, these findings would provide further evidence that adaptation in VR occurs rapidly (Fransson et al., 2019). Additionally, these findings would provide researchers and practitioners with meaningful insights for designing effective familiarization protocols and utilizing performance assessments that reflect true skill development rather than novelty effects.

Aims & Hypotheses

The primary aim of the present study was to investigate the effects of virtual reality immersion on motor behavioral (e.g., completion time, success rate, cadence, speed, & power), physiological (e.g., heart rate), and psychological (e.g., RPE, intrinsic motivation, & engagement) factors across multiple practice sessions. Building on the previous study (Velten, 2024), which collected all metrics at the completion of each trial, the present study collected all behavioral and physiological variables, as well as RPE, at 1000-meter intervals (i.e., laps) within each 8000-meter trial to capture potential learning effects. A secondary aim of the present study was to further investigate if the aforementioned metrics diminished over time with repeated exposures to VR with differing levels of immersion.

Motor Behavioral Hypotheses

Although the results of study 1 (Velten, 2024) were only partially consistent with the findings reported by Juliano and Liew (2020), it was hypothesized that without the technological limitations of the projection, there would be no significant differences in motor behavioral measures between conditions (e.g., completion time, success rate, cadence, speed, & power). Additionally, it was hypothesized that the additional days of practice would reveal a speed-accuracy tradeoff (Fitts, 1954). Specifically, if participants completed the task faster over time, their success rate (i.e., percentage of tokens collected) was expected to decrease. Alternatively, if their success rate increased over time, their completion time was expected to decrease (i.e., they would get slower). In the absence of a speed-accuracy tradeoff, it was hypothesized performance would remain unchanged across days which would be realized with a lack of significant differences between days of practice.

Physiological Hypotheses

Based on findings from study 1 (Velten, 2024), it was hypothesized that there would be no significant differences in physiological measurements (e.g., heart rate) between conditions. Although Malińska et al. (2015) found IVR to be associated with higher sympathetic nervous system activation, characterized by increased heart rate variability measured via electrocardiogram, the results of study 1 (Velten) and previous research by Lohse et al. (2016) suggest that the equally game-like designs in the NIVR and IVR conditions are comparably engaging and therefore will not impact physiological responses differently.

Psychological Hypotheses

Based on findings from Frederikson et al. (2020), Markwell et al., (2023), Polechoński et al. (2024) and study 1 (Velten, 2024), it was hypothesized that there would be significant differences in the psychological measurements of rated perceived exertion (RPE) and intrinsic motivation. Specifically, it was predicted that participants would report greater RPE and intrinsic motivation in the IVR condition relative to the NIVR condition. This difference in RPE was expected to be observed from the first data collection point at 1000-meters on the first day of each condition and across all subsequent data collection points which occurred every 1000-meters within each condition. While this difference was expected to remain significant between conditions across data collection points and days of participation, it was hypothesized that RPE would decrease from the first to the second day *within* each condition (i.e., NIVR Day 1 RPE was expected to be higher than NIVR Day 2 and IVR Day 1 RPE was expected to be higher than IVR Day 2). Sparrow and colleagues (1999) provide support for this hypothesis, finding that reported RPE decreased across practice sessions of a self-paced rowing task when there was no significant difference in the power outputs of each practice session. Although Keller and Suzuki (2004) suggest that motivational benefits may diminish with repeated exposure, differences in intrinsic motivation were expected to persist based on findings from Jeno and colleagues (2019) and Markwell (2023, experiment 2).

Lohse et al. (2016) suggests game-like VR designs are more engaging than sterile environments. Since the NIVR and IVR conditions were equally game-like, it was predicted that they should be comparably engaging. Results from study 1 (Velten, 2024) further support this assumption, as no significant differences in measures of engagement were found between conditions. Therefore, it was hypothesized that there would be no significant differences in measures of engagement between conditions in the present study.

If these predictions were supported, it would suggest that VR immersion does not significantly impact motor behavioral or physiological outcomes but does significantly impact psychological factors in the performer. These findings would help researchers, practitioners, and VR developers make informed decisions about which types of VR technology to utilize to achieve specific outcome goals.

Method

Participants

A total of 23 university students volunteered to participate in the present study. One participant was excluded from participation due to their PAR-Q results, and two participants were excluded from analyses due to partial study completion. Of the remaining 20 participants included in the analyses, 11 were female and nine were male, ranging in age from 18-27 (M_{age} = 20.90, SD_{age} = 2.38). Participants were excluded for scores exceeding 25 on the Motion Sickness Susceptibility Questionnaire short-form (MSSQ-short), if they answered “yes” to any of the questions on the Physical Activity Readiness Questionnaire (PAR-Q), or if they participated in study 1 (Velten, 2024). Additionally, participants were excluded from the study if their heart rate exceeded the maximum safe cutoff during participation, which was predetermined by subtracting their age from 220. An *a priori* power analysis was performed using G*Power statistical power analysis software version 3.1.9.6 to determine a recommended minimum sample size prior to recruitment. The analysis was based on a within factors repeated measures analysis of variance (ANOVA), assuming a medium effect size (f = 0.50), an alpha level of 0.05, and desired power of 0.80. The analysis yielded a recommended minimum sample size of 35 participants. However, after data collection began, linear mixed model analyses conducted with the first twelve participants suggested a recommended sample range of 24-34 participants.

Task and Apparatus

All data collection for this experiment took place in a climate-controlled research laboratory. Identical to study 1 (Velten, 2024), a WahooKICKR indoor stationary bicycle (Wahoo Fitness, Georgia, United States) was used in both conditions. All participants underwent a standardized procedure to determine proper bike fit. Measured manually using a handheld metal goniometer, the saddle height was adjusted so that the participant's knee flexion angle was approximately 25-30° with the pedal at the dead bottom position (180°) (Bini et al., 2011; Hummer et al., 2021). Using a plum bob with the pedal at the dead bottom position, the saddle fore-aft position was set to align the patella with the pedal spindle (Fang et al., 2016; Gardner et al., 2015; Hummer et al., 2021). The handlebar position was adjusted so that the participant's trunk angle was 90° with the axis at the iliac crest (Fang et al., 2016; Hummer et al., 2021).

The MSSQ-Short and PAR-Q questionnaires were used to determine participant eligibility. The MSSQ-Short (Appendix A) was used to determine participant susceptibility to motion sickness, defined by feelings of queasiness, nausea, or actual vomiting. Participants were asked to indicate how often they felt sick or nauseated on a numerical rating scale of 0-3 anchored by "never felt sick" and "frequently felt sick". Participants were excluded for scores exceeding 25 on the MSSQ-Short. The PAR-Q (Appendix B) was used to screen participants for evidence of risk factors and recent injuries. If a participant answered "yes" to any of the general screening questions, which would indicate a medical risk factor or recent injury, they were excluded from participation. Participants who completed study 1 (Velten, 2024) were not eligible to participate in the present study.

Participants performed a total of four 8000-meter trials on four separate days within a two-week time frame and each session separated by at least 72 hours. Two conditions were utilized for the present study: a non-immersive virtual reality (NIVR) environment and an immersive virtual reality (IVR) environment. Participants completed two consecutive trials in one condition followed by two consecutive trials in the other condition. The order of conditions was counterbalanced.

The NIVR trials were completed utilizing a tablet running on Android OS displayed between and over the handlebars of the bike utilizing a Mippko tablet holder with a gooseneck arm and crab clamp (Figure 14). The tablet utilized stored data during operation, rather than a wireless internet connection, which provided a more stable connection to the cycling application than the methods utilized in study 1 (Velten, 2024). This ensured visual information delivered to the user was never disrupted, allowing for more accurate perception-action coupling and movement execution within the application. The IVR trials were completed using the Meta Quest 2 virtual reality headset. Participants were informed that the course was set to a fixed distance and that researchers would measure the number of tokens, which were represented as a T in the application, collected and time to completion (Appendix E). Participants were not made aware of the other dependent measures being collected by the bike or questionnaire.

Both virtual reality conditions were designed using the cross-platform game engine Unity 3D (Version 2022.3.16). The applications were designed to give the user consistent experiences across immersive and non-immersive platforms. The cycling scene featured a low-poly virtual environment designed to appear endless to the user. The user remained fixed in one of three lanes but could switch lanes using the corresponding buttons on the Wahoo bike. Pedaling propelled the user forward, with the application progressing at a speed that matched the user’s pedaling rate. Tokens were scattered across the lanes, and users collected points by pedaling through them. The user's perspective was consistent across applications, maintaining a first-person viewpoint in the NIVR condition without the use of grounding elements such as an avatar or handlebars. All participants were physically seated in the same position on the same indoor stationary bicycle for all four days of participation. The only difference between the NIVR and IVR condition was the use of the HMD in the IVR condition (see Figure 15), which alters participants' field of view of the cycling scene.

Figure 14. Experiment two: NIVR condition.

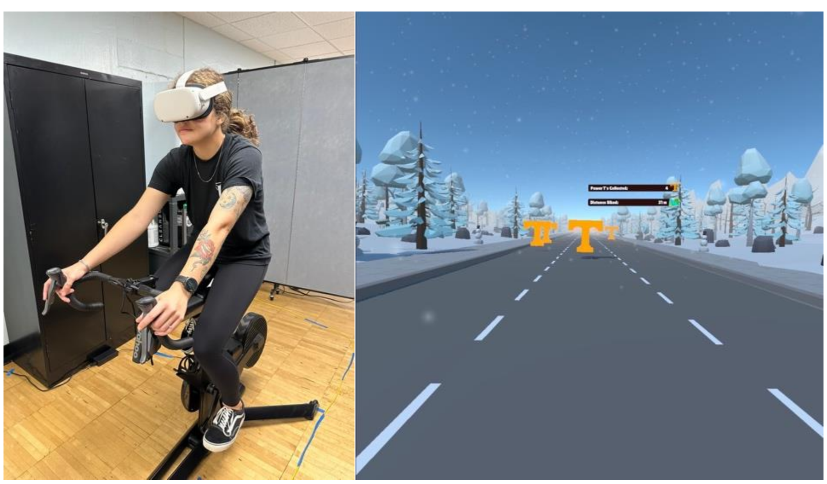

Figure 15. Experiment Two: IVR condition. The image on the right side of the panel provides an example of the animation the participant observed inside the IVR headset.

Motor Behavioral Measurements

Course completion time was recorded in seconds (s) via the cycling course application. Success rate was calculated by dividing the number of tokens collected by the total number of tokens that were made available to the participant. Token location across the three lanes was randomized, and tokens were generated at a rate proportional to participants' movement speed, resulting in a relatively consistent number of tokens per meter traveled. Average speed was recorded in kilometers per hour (kph), cadence in revolutions per minute (RPM), and power output in watts (W) via the WahooKICKR

Physiological Measurements

Participants were equipped with a Polar Verity Sense optical heart rate sensor strapped to their right arm. Using the manufacturer-provided armband, the sensor was positioned on the posterior aspect of the upper arm approximately five centimeters above the olecranon process. Average heart rate was recorded in beats per minute (bpm).

Psychological Measurements

Participants' experiences were measured via the Intrinsic Motivation Inventory (IMI) and Engagement Scale Questionnaire (ESQ). The IMI (Appendix C) contains statements related to six subscales: Interest/Enjoyment, Perceived Competence, Effort, Value/Usefulness, Pressure/Tension, and Perceived Choice. Participants were asked to indicate how true each statement was on a numerical rating scale of 1-7 anchored by "not at all true" and "very true." The ESQ (Appendix D) contains statements related to three subscales: behavioral engagement, cognitive engagement, and emotional engagement. Participants were asked to indicate the extent to which they agree with each statement on a numerical rating scale of 1-5 anchored by "strongly disagree" and "strongly agree." Additionally, participants were asked to verbally indicate their

RPE every 1000 meters and immediately following completion of the task on a rating scale of 1-10 anchored by “hardly any exertion” to “it feels almost impossible to keep going.”

Procedure

Approval from the University’s Institutional Review Board (IRB-22-06810-XP) was obtained prior to participant recruitment. Participants were recruited from a variety of courses in the Department of Kinesiology, Recreation, and Sport Studies at the University of Tennessee. After providing informed consent, participants completed the MSSQ-short and PAR-Q questionaries. Participants were excluded for scores exceeding 25 on the MSSQ-short or if they answered “yes” to any of the questions on the PAR-Q. Next, participants’ maximum safe heart rate was calculated by subtracting their age from 220. If participants’ heart rate exceeded this number at any point during the four research sessions, their participation would have been stopped. No participant reached this threshold during participation. The bike was then fitted to the participants’ unique measurements and participants were equipped with a heart rate monitor strapped around the arm.

This study utilized a within-participant experimental design, with all participants completing each condition. The order in which participants completed the experimental conditions (i.e., NIVR or IVR) was counterbalanced to minimize order effects. After the bike and heart monitor were fitted to the participant, they completed a pre-test IMI. The researcher then verbally read standardized instructions for the cycling task to the participant (Appendix E). Participants were informed that researchers would record the number of tokens collected and time to completion, but they were not made aware of the other dependent measures being collected by the bike and questionnaires. Participants were also informed that the researcher would ask for their RPE every 1000 meters on a rating scale of 1-10 anchored by “hardly any exertion" to "it feels almost impossible to keep going." After these initial instructions were provided and pre-test surveys completed, participants then completed the task in either the NIVR or IVR condition. Following task completion, participants completed the post-test IMI and ESQ in a counterbalanced order.

Following the first day of participation, participants returned every three to five days for up to two weeks to complete the remaining days of participation. On day two, participants followed the same procedure as day one. Days three and four mimicked days one and two of participation for the other experimental condition (i.e., NIVR or IVR). Previous research has shown that individuals who utilized VR therapy reported greater levels of enjoyment (Adamovich et al., 2009) and increased satisfaction with rehabilitation (Wiley et al., 2022) regardless of performance outcomes, which may be an important factor affecting adherence. Therefore, following completion on the fourth and final day of testing, participants were verbally asked, "Having practiced two days with the tablet and two days in the Oculus headset, which did you prefer?" The researcher recorded participants' verbal response to this question. Participants then returned all equipment and were thanked for their participation.

Data Analysis

All data collected in this study was analyzed using IBM SPSS Statistics version 29.0.2.0. The effect of condition (i.e., NIVR or IVR) on behavioral, physiological, and psychological measures was evaluated using linear mixed-effects models (LMMs). Linear mixed models are well-suited for the repeated-measures structure of this data set. Unlike repeated-measures analysis of variance (ANOVAs), LMMs do not exclude cases with missing data points. Separate LMMs were ran for each dependent variable, including completion time, success rate, speed, cadence, power, heart rate, and RPE. Each model included Condition (i.e., NIVR or IVR), Condition Order, and Laps (i.e., 1000-meter increments up to 8000-meters) as fixed effects, with Laps and Day treated as repeated measures and Participant specified as a random effect. Residuals were examined across all variables for normality. All metrics were normally distributed.

A separate set of LMMs was used to assess intrinsic motivation, including global IMI and each of the six IMI subscales (Interest/Enjoyment, Perceived Competence, Effort/Importance, Pressure/Tension, Perceived Choice, and Value/Usefulness), and engagement. In these models, Condition (NIVR or IVR), Condition Order, and Time (Pre/Post) were treated as fixed effects, with Condition and Laps treated as repeated measures and Participant specified as a random effect. Results from the LMM analyses are reported below.

Results

Linear mixed models (LMMs) were used to assess all measurements across conditions and days of participation. Preliminary LMMs with Condition (NIVR or IVR) and Condition Order as fixed effects and Participants specified as a random effect indicated no evidence of carryover effects. Additional LMMs with Condition and Day (nested within Condition) as fixed effects and Participant specified as a random effect indicated there were no significant differences between the first and second day of participation within each condition. Therefore, data was averaged across days within each condition to reduce model convergence issues. Results for motor behavioral, physiological, and psychological measurements are detailed in the sections that follow.

Motor Behavioral Measurements

Separate LMMs were conducted to assess completion time, success rate, speed, cadence and power. Each model included Condition (NIVR or IVR), Condition Order, and Laps (1000-

meter increments up to 8000-meters) as fixed effects, with Condition and Laps treated as repeated measures and Participant specified as a random effect. There were no significant main effects for condition or condition order for any of the motor behavioral measurements (see Table 6).

Table 6. Means and standard deviations for behavioral measurements.

Measure	NIVR Mean (SD)	IVR Mean (SD)
Completion Time (s)	227.63 (42.80)	222.92 (37.65)
Success Rate (%)	54.30 (3.32)	54.80 (3.50)
Average Speed (kph)	14.78 (0.93)	15.12 (1.06)
Average Cadence (rpm)	80.29 (12.97)	82.05 (14.00)
Average Power (W)	68.68 (17.58)	71.20 (18.18)

Condition x Lap interaction was significant for speed ($F(7, 132.71) = 2.26$, $p = .03$), cadence ($F(7, 133.19) = 2.62$, $p = .01$), and power ($F(7, 134.84) = 2.62$, $p = .01$). Least Significant Difference (LSD) post-hoc pairwise comparisons were not significant for speed or cadence but indicated statistically significant differences at laps four and five for power, with the IVR condition resulting in significantly greater power at those time points compared to the NIVR condition (see Table 7).

Table 7. Post-hoc Pairwise Comparisons for condition x lap interactions for speed, cadence, and power. The * in the above table indicates a significant difference between conditions at laps 4 and 5 for power.

Lap	Speed p-value	Cadence p-value	Power p-value
1	.93	.92	.47
2	.51	.55	.36
3	.09	.09	.12
4	.05	.05	.02*
5	.06	.06	.02*
6	.11	.13	.06
7	.37	.47	.19
8	.58	.72	.55

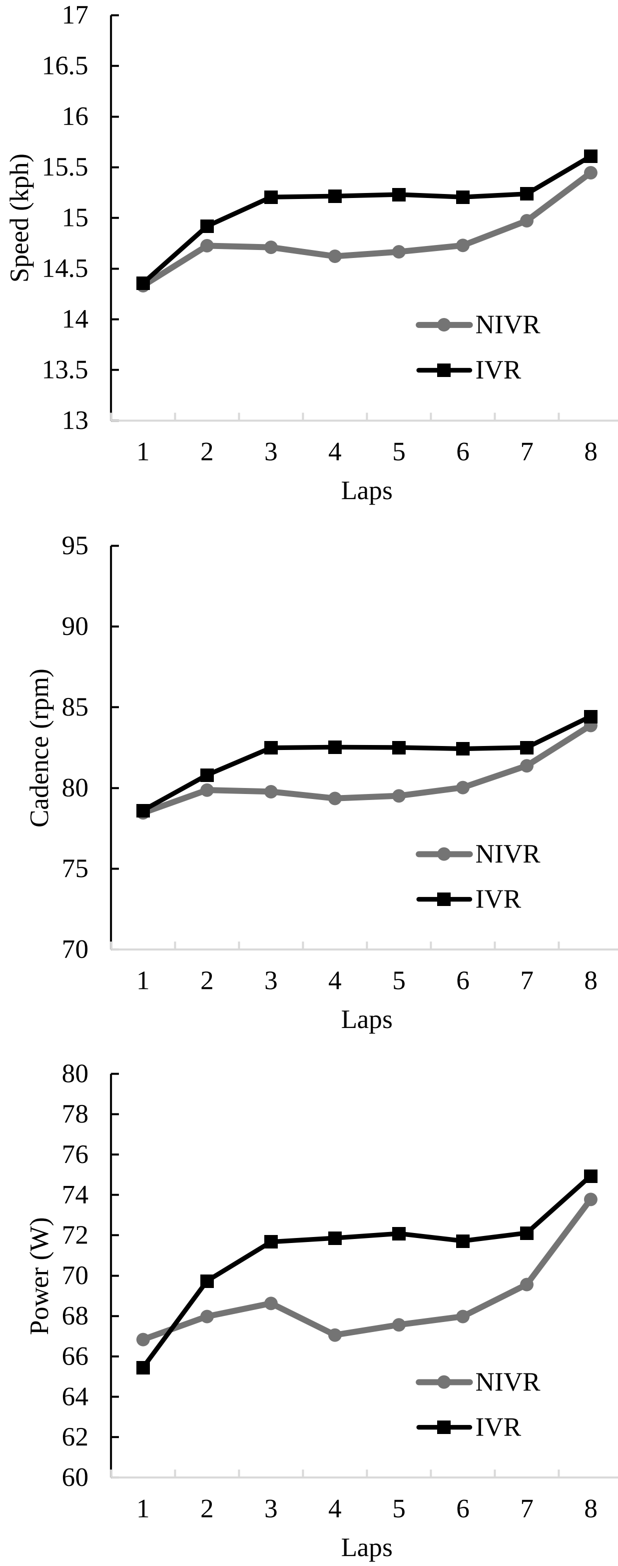

Figure 16. Average speed, cadence, and power for each condition across laps. Each lap represents 1000-meters in cycled distance.

Although pairwise comparisons were not significant for speed and cadence, post hoc trends across all three variables suggest laps three through six were the primary points of divergence between conditions, with the IVR condition trending higher across these time points (see Figure 16). Condition x Lap interactions were not significant for completion time or success rate.

Physiological Measurements

A separate LMM was conducted to assess heart rate. The model included Condition (NIVR or IVR), Condition Order, and Laps (1000-meter increments up to 8000-meters) as fixed effects, with Condition and Laps treated as repeated measures and Participant specified as a random effect. No significant main effects or interactions were observed (see Table 8). The mean average heart rate for the NIVR condition was 132.33 bpm (SD_{NIVR} = 21.45) and for the IVR condition was 136.03 bpm (SD_{IVR} = 19.67).

Table 8. Linear Mixed Model results for heart rate.

Effect	df	F	p-value
Condition	(1, 18.96)	3.68	.07
Condition order	(1, 18.03)	0.001	.97
Condition x Laps	(7, 138.81)	1.19	.31

Psychological Measurements

A separate LMM was conducted to assess RPE. The model included Condition (NIVR or IVR), Condition Order, and Laps (1000-meter increments up to 8000-meters) as fixed effects, with Condition and Laps treated as repeated measures and Participant specified as a random effect. No main effect for Condition or any interactions were observed. There was however a significant main effect of Laps ($F(7, 120.53) = 31.43$, p = <.001), indicating RPE increased from lap one to lap eight in both conditions. There was also a main effect of condition order ($F(1, 16.2) = 8.11$, $p = .01$), indicating higher RPE during the first condition, regardless of which condition was completed first. Although not statistically significant, values were consistently higher on average in the IVR condition across all laps (see Figure 17).

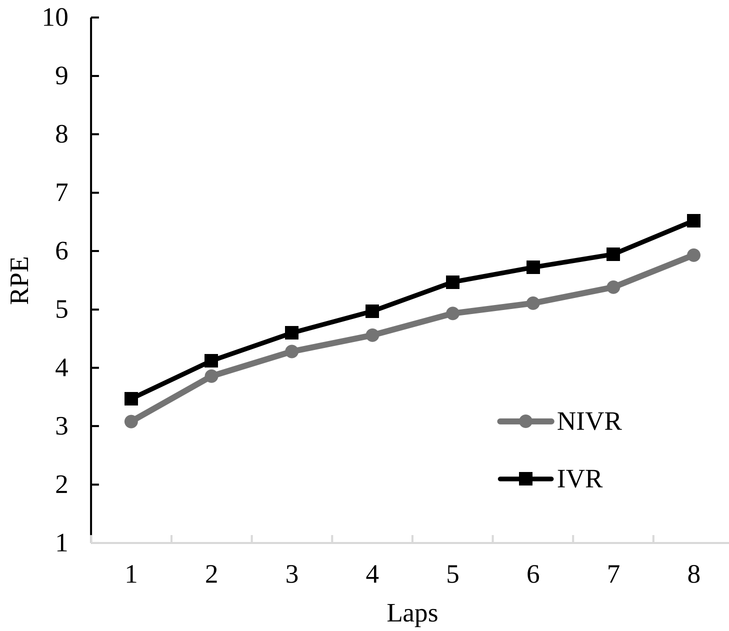

Figure 17. Average RPE for each condition across laps. Each lap represents 1000-meters in cycled distance.

A separate set of LMMs was used to assess intrinsic motivation, including global IMI and each of the six IMI subscales (Interest/Enjoyment, Perceived Competence, Effort/Importance, Pressure/Tension, Perceived Choice, and Value/Usefulness). In these models, Condition (NIVR or IVR), Condition Order, and Time (Pre/Post) were treated as fixed effects, with Condition and Time treated as repeated measures and Participant specified as a random effect. No significant main effects or interactions were observed for global IMI, Effort/Importance, and Perceived Choice. There was a significant main effect of condition order for Perceived Competence ($F(1, 18) = 6.86$, $p = .02$) and Pressure/Tension ($F(1, 18) = 13.98$, $p = .002$), indicating higher Perceived Competence scores and lower Pressure/Tension scores during the second condition, regardless of which condition was completed first. Additionally, there was a significant main effect of time for Interest/Enjoyment (F(1, 21.69) = 8.14, p = .009) and Value/Usefulness (F(1, 21.32) = 11.12, p = .003), indicating higher Interest/Enjoyment and higher Value/Usefulness post-test scores compared to pre-test scores for both conditions.

Table 9. Means and standard deviations for psychological measurements.

Measure	NIVR Mean (SD)	IVR Mean (SD)
RPE	4.64 (1.69)	5.10 (1.70)
Engagement	4.31 (0.50)	4.33 (0.51)
Pre-test IMI	4.61 (0.58)	4.59 (0.72)
Post-test IMI	4.75 (0.58)	4.75 (0.72)
Pre-test IMI - Interest/Enjoyment	3.99 (1.24)	3.87 (1.40)
Post-test IMI - Interest/Enjoyment	4.23 (1.24)	4.41 (1.40)
Pre-test IMI - Perceived Competence	4.64 (0.98)	4.61 (1.19)
Post-test IMI - Perceived Competence	4.79 (0.98)	4.66 (1.19)
Pre-test IMI - Effort/Importance	5.72 (1.07)	5.72 (1.03)
Post-test IMI - Effort/Importance	5.80 (1.07)	5.88 (1.03)
Pre-test IMI - Pressure/Tension	2.11 (0.93)	2.25 (0.96)
Post-test IMI - Pressure/Tension	2.11 (0.93)	2.15 (0.96)
Pre-test IMI - Perceived Choice	6.11 (0.85)	6.09 (0.90)
Post-test IMI - Perceived Choice	6.09 (0.85)	6.12 (0.90)
Pre-test IMI - Value/Usefulness	5.07 (1.19)	5.03 (1.29)
Post-test IMI - Value/Usefulness	5.41 (1.19)	5.29 (1.29)

A separate LMM was used to assess engagement. Condition (NIVR or IVR) and Condition Order were treated as fixed effects, with Condition treated as a repeated measure and Participant specified as a random effect. No significant main effects or interactions were observed (see Table 10).

Table 10. Linear Mixed Model results for engagement.

Effect	df	F	p-value
Condition	(1, 18)	0.05	.83
Condition order	(1, 18)	0.42	.53
Condition x condition order	(1, 18)	0.02	.91

Experiment 2 Discussion

The present study investigated the effects of virtual reality immersion on motor behavioral (e.g., completion time, success rate, cadence, speed, & power), physiological (e.g., heart rate), and psychological (e.g., RPE, intrinsic motivation, & engagement) factors across multiple practice sessions. Study 2 expanded on the previous study (Velten, 2024) by adding an extra day of practice in each condition and collecting all behavioral and physiological variables, as well as RPE, at 1000-meter intervals during each 8000-meter trial rather than solely upon completion of each 8000-meter trial. It was hypothesized that there would be no significant differences in motor behavioral and physiological measurements between conditions, but that there would be significant differences in psychological measurements, specifically that these measures would be greater in the IVR condition compared to the NIVR condition. Furthermore, it was hypothesized that the additional day of practice for each condition would not diminish these differences. The results of this study mostly supported these hypotheses. A more detailed explanation of the results of the experiment 2 will be provided in the following sections.

Motor Behavioral Measurements

Based on previous findings by Juliano and Liew (2020), and considering the technological limitations of study 1 (Velten, 2024), it was hypothesized that there would be no significant differences in motor behavioral measures (e.g., completion time, success rate, cadence, speed, & power) between conditions. These predictions were mostly supported. Specifically, the analyses revealed no significant differences in completion time, success rate, speed, cadence, or power between conditions. These results are congruent with previous research by Juliano and Liew (2020) suggesting skill progression occurs at a similar rate in both immersive VR and screen environments. In the present study, the VR applications were designed to give the user consistent experiences across immersive and non-immersive platforms, and the task instructions were standardized across conditions, which likely contributed to the lack of differences between conditions. Additionally, both conditions in the present study utilized the same game-like task. Lohse et al. (2016) found a gamified environment improved participant speed and accuracy compared to a sterile environment. However, due to the nature of this task requiring participants to balance speed (i.e., completion time) and accuracy (i.e., success rate) (see Appendix E), it was hypothesized that the additional day of practice in each condition would reveal a speed-accuracy tradeoff (Fitts, 1954). In other words, if participants completed the task faster over time, their success rate was expected to decrease (i.e., collect a smaller percentage of tokens). Alternatively, if their success rate increased over time (i.e., collect a larger percentage of tokens), their completion time was expected to increase (i.e., they would get slower). In the absence of a speed-accuracy tradeoff, it was hypothesized performance would remain relatively consistent across days. These hypotheses were partially supported. Analyses revealed no significant differences in completion time, success rate, cadence, speed, or power across days of participation. According to Fitts' Law (Fitts, 1954), a speed-accuracy tradeoff would be expected if participants altered their speed across days of participation. However, results indicated that participant speed remained relatively constant across all four days of participation. Consequently, overall task performance, including both completion time and success rate, remained relatively stable as predicted. Because neither speed (i.e., completion time) nor accuracy (i.e., success rate) changed with practice, evidence of a speed-accuracy tradeoff was not observed. Therefore, the results of the present study do not provide sufficient evidence to determine if Fitts' law (Fitts, 1954) applies to this task.

Although overall performance measures did not differ between conditions, there was a significant Condition x Lap interaction for speed, cadence, and power. Post-hoc pairwise comparisons indicated that these differences emerged specifically across laps three through six (see Figure 15). In the IVR condition, these metrics continued to trend upward across all laps, while in the NIVR condition, they temporarily decreased at these time points before rising again in the final two laps. While these findings are somewhat surprising given the consistent nature of the cycling task, findings reported by Winter and colleagues (2021) may provide further insight to help interpret this observation. When testing a treadmill training protocol for gait rehabilitation, walking speed differed between IVR and monitor training conditions despite no corresponding differences in heart rate (Winter et al., 2021), similar to the findings reported in the present study. Participants in the IVR condition also reported higher mood, motivation, and sense of presence, as well as faster subjective perception of elapsed time compared to the monitor and traditional (i.e., no-VR or monitor) training conditions (Winter et al., 2021). Although the present study did not find significant differences in motivation between conditions, it is possible that a heightened sense of presence or altered perception of time in the IVR condition influenced participant behavior during the middle portion of the task. As evidence of this possibility, one recent study suggests that immersive VR exclusively alters judgements of time related to the duration of physical processes (e.g., the completion of a 1000-meter interval in the present study) rather than perceptions of abstract time (e.g., 8 seconds) (Bogon et al., 2024). However, because the present study did not measure perceptions of presence or subjective measures of time, this interpretation remains speculative and warrants further investigation to validate this possibility. Future studies investigating VR immersion should include presence and subjective perception metrics to more clearly evaluate their potential influence on behavior.

Physiological Measurements

Although previous research has found IVR to be associated with higher sympathetic nervous system activation, characterized by increased heart rate variability (Malińska et al., 2015), it was hypothesized that there would be no significant differences in physiological measurements (e.g., heart rate) between conditions based on findings from study 1 (Velten, 2024). This hypothesis was supported. There were no significant differences in average heart rate between conditions or between days of participation. These results are further supported by the findings of the behavioral metrics detailed in the previous section. No significant differences were observed in completion times, success rate, speed, cadence, or power output between conditions; thus, heart rate would be expected to remain relatively constant as well. Although these results contradict the findings reported by Malińska and colleagues (2015), it should be noted that their study utilized passive exposure to a stimulus while the present study utilized a goal-directed continuous motor task. The lack of significant differences observed in heart rate, together with the lack of differences observed in behavioral characteristics (i.e., speed, cadence, and power), suggests that participants maintained comparable levels of physiological effort across conditions in both studies of the present dissertation. These observations indicate that when the physical and perceptual demands of a task are consistent across platforms, immersion alone is not enough to change the user's physiological workload. This provides researchers and practitioners with valuable insights for effective task design across modalities, emphasizing the importance of considering task demands and characteristics, regardless of level of immersion.

Psychological Measurements

Previous research suggests perceptions of exertion may be higher in IVR compared to NIVR and traditional training environments (Frederikson et al., 2020; Naugle et al., 2024). Therefore, it was hypothesized that there would be significant differences in RPE between conditions. This difference in RPE was expected to be observed from the first data collection point at 1000-meters on the first day of each condition. While this difference was expected to remain significant between conditions across days of participation, it was hypothesized that RPE would decrease from the first to the second day *within* each condition based on previous findings by Sparrow and colleagues (1999). These hypotheses were partially supported. The results of the present study indicated that there were no significant differences in RPE between conditions. Although not statistically significant, RPE values were consistently higher in the IVR condition compared to the NIVR condition across all laps (see Figure 17). Though not statistically significant, these results are consistent with previous research findings that RPE is higher in IVR conditions compared to NIVR or traditional training environments (Frederikson et al., 2020; Naugle et al., 2024; Velten, 2024). Additionally, the analysis revealed a condition order effect in which participants reported significantly higher RPE during the first condition (days 1 & 2) compared to the second condition (days 3 & 4), regardless of which condition was completed first. Although this finding does not align with the proposed hypothesis, it is consistent with Sparrow and colleagues (1999) findings suggesting that task familiarity may lead to decreased perceptions of exertion over time. Interestingly, RPE increased at a relatively steady rate across both conditions, remaining elevated during the middle portion of the task in the NIVR condition even as speed, cadence, and power temporarily decreased. One possible explanation is that perceptions of effort may be more closely related to cumulative performance than short-term performance fluctuations. Previous research suggests time on task influences perceptions of exertion, specifically that perceptions of exertion show fewer fluctuations (e.g., downward shifts) at higher workloads (Balagué et al., 2015). Based on these findings, it is possible that participants in the present study performed the task at a high enough workload for RPE fluctuations to be minimized. The results of the present dissertation provide evidence that virtual reality practice impacts cumulative perceptions of exertion more than moment-to-moment fluctuations during a moderate intensity continuous activity. Altogether, these findings suggest that perceptions of exertion may be influenced by the demands of the task itself and repeated task exposure rather than by immersion level alone.

In addition to differences in RPE, it was hypothesized that there would be significant differences in intrinsic motivation between conditions. Based on findings from Markwell et al. (2023), Polechoński et al. (2024) and study 1 (Velten, 2024), it was predicted that participants would report greater intrinsic motivation in the IVR condition relative to the NIVR condition. Additionally, differences in intrinsic motivation were expected to persist across days of participation. These hypotheses were not supported. Markwell et al. (2023) and study 1 (Velten, 2024) reported that participants experienced significantly greater intrinsic motivation in the IVR condition. However, the present study does not lend further support to these findings. Alternatively, Keller and Suzuki (2004) proposed that motivational benefits may be driven by a novelty effect that diminishes with repeated exposure. However, the results of the present study do not align with this explanation. In the present study, intrinsic motivation remained relatively stable across days of participation, suggesting both environments were similarly motivating from the first exposure rather than that exposure diminishing motivation over time. The results for the IMI subscales may provide further context to assist in the interpretation of this finding. Although global IMI did not differ between conditions, there was a significant condition order effect for the Perceived Competence and Pressure/Tension subscales. Specifically, participants reported higher perceived competence and lower pressure/tension during the completion of the second condition (days 3 & 4) compared to the first condition (days 1 & 2), regardless of which environment they completed first. This tradeoff pattern is consistent with previous research findings that practice can enhance perceptions of competence and reduce performance-related stress (Chiviacowsky et al., 2012; Ryan & Deci, 2000). Additionally, there was a significant effect of time for the Interest/Enjoyment and Value/Usefulness subscales. Participants reported increased interest/enjoyment and value on the post-test compared to the pre-test across conditions. This time effect may reflect the growing feelings of competence described above, suggesting that the development of mastery through practice may contribute more to the user experience rather than level of immersion alone. These results align with the predictions of Self-Determination Theory (Ryan & Deci, 2000), which highlights feelings of competence as a key pillar of intrinsic motivation. It also provides further support that repeated practice and resulting increased feelings of mastery would contribute more to enjoyment and value of the task than level of immersion within a virtual environment. Future studies should investigate perceptions of competence and mastery in greater depth to better understand these nuanced motivational dynamics in VR.

Lohse et al. (2016) proposed game-like designs are more engaging than sterile environments. The methodology of the present study and the results from study 1 (Velten, 2024) support the assumption that the NIVR and IVR conditions utilized in the present study were equally game-like and thus should be equally engaging. Therefore, it was hypothesized that no significant differences in measures of engagement would be found between conditions. This hypothesis was supported. These results are consistent with previous findings by Markwell and colleagues (2023) and study 1 (Velten, 2024), which found no differences in measures of engagement. Altogether, these results suggest that level of immersion alone does not create a more engaging environment for the user. Future studies should investigate these effects in the absence of a game-like design to better understand how task design may impact user engagement in VR.

Summary and Future Directions

The present study sought to determine how virtual reality immersion affected motor behavioral (e.g., completion time, success rate, cadence, speed, & power), physiological (e.g., heart rate), and psychological (e.g., RPE, intrinsic motivation, & engagement) factors across multiple practice sessions by having participants complete the same stationary cycling task twice in both a non-immersive and immersive virtual reality environment. Consistent with previous research, there were no significant differences in completion time (Fitts, 1954; Velten, 2024), success rate, cadence (Velten, 2024), speed (Fitts, 1954; Velten, 2024), power (Velten, 2024), heart rate (Velten, 2024), or engagement (Lohse et al., 2016; Markwell et al., 2023; Velten, 2024) between conditions. However, a Condition x Lap interaction emerged for measures of speed, cadence, and power, suggesting pacing during the middle portion of the task differed between conditions. Interestingly, RPE increased at a relatively steady rate across both conditions, remaining elevated during the middle portion of the task in the NIVR condition even as speed, cadence, and power temporarily decreased. In contrast to previous findings (Frederikson et al., 2020; Markwell et al., 2023; Velten, 2024), the present study did not find any significant differences in global IMI or any of the six IMI subscales between conditions.

The present study addressed key limitations in the existing literature. First, by creating and implementing identical, first-person perspective virtual reality practice conditions, direct comparisons between non-immersive and immersive simulations were enabled. Additionally, key technology limitations in study 1 (Velten, 2024) were addressed, allowing for more accurate perception-action coupling and movement execution within the application. This facilitated more accurate performance assessment and comparisons across conditions. While the lack of significant differences in psychological measurements between conditions of the present study did not align with findings by Jeno and colleagues (2019) and Markwell (2023), the results do provide additional evidence that the effects of immersion are more nuanced and are not simply due to a novelty effect, as some earlier researchers (Keller & Suzuki, 2004) have suggested.

As with any study, the findings of the present project should be considered in light of some limitations. Although the recommended sample size range was 24-34 participants, only 20 participants were included in the final analyses. Residuals were normally distributed but this smaller than projected sample size may have reduced statistical power, making it more difficult to discern true effects. Additionally, the sample of participants were relatively homogonous. All participants were from the same campus department, close in age, and all regularly active individuals. While the present study expanded on the findings of study 1 by adding a second day of practice in each condition, the two-day duration of practice does limit the generalizability of the findings. This raises questions about the potential effects of more long-term practice exposure. Furthermore, the present study utilized a single stationary cycling task, which may further limit the generalizability of findings. Future research should include more diverse populations and a wider variety of tasks to increase the applicability of these results.

In conclusion, the present study offers meaningful contributions to the existing body of research on motor behavioral, physiological, and psychological outcomes associated with practicing in virtual reality. The present study extends previous research (e.g., Frederikson et al., 2020; Juliano & Liew, 2020; Polechoński et al., 2024) by experimentally comparing non-immersive and immersive virtual reality environments across multiple days of practice. Furthermore, the addition of several data collection points at fixed intervals throughout each trial facilitated a better understanding of the more nuanced behavioral changes that may be present during completion of a task in VR. Altogether, the findings of the present study suggest immersion may impact within-task dynamics more than between-task performance. These results provide researchers and practitioners with meaningful insights regarding how users exert effort and regulate motor behavior throughout the performance of a continuous task when utilizing VR practice.

GENERAL DISCUSSION

Virtual reality (VR) is one of the most rapidly advancing technologies that exists today. Over the last two decades, there has been a substantial increase in research papers across several disciplines (Cipresso et al., 2018), and it's estimated market size exceeds $20 billion in the gaming industry alone (Grand View Research, 2023). Researchers and practitioners alike have turned to this technology as an alternative or supplement to traditional training, especially in cases where real-world (RW) training is overly expensive, hazardous, or involves finite resources (Kavanagh et al., 2017). While the current body of literature spans across several disciplines and populations, inconsistences in defining "virtual reality" have complicated the application of results. For example, some studies have defined "virtual reality" as fully immersive environments delivered through head-mounted displays (HMDs) (Gray, 2017; Michalski et al., 2019b), while others have used the term to describe non-immersive environments delivered through a projected flat screen or a television or computer monitor (Bao et al, 2013; Tirp et al., 2015). While both non-immersive (NIVR) and immersive (IVR) environments have demonstrated positive transfer to RW tasks independently (Adamovich et al., 2009; Bao et al, 2013; Gray, 2017; Michalski et al., 2019b; Rauter et al., 2013; Tirp et al., 2015; Torkington et al., 2001), there are only a few studies which have directly compared NIVR and IVR environments (Frederikson et al., 2020; Juliano & Liew, 2020; Polechoński et al., 2024). As VR continues to advance, understanding how the level of VR immersion impacts performance is critical to effective practical application, especially given the variability in the existing findings (Frederikson et al., 2020; Juliano & Liew, 2020; Polechoński et al., 2024). For example, Frederikson and colleagues (2020) observed significantly greater cognitive load when participants were in a fully immersive condition, whereas Polechoński and colleagues (2024) found a fully immersive condition elicited significantly greater feelings of enjoyment and flow. Considering so few studies have directly compared the performance efficacy of IVR and NIVR environments, experiments one (Velten, 2024) and two of the present dissertation investigated the effects of virtual reality immersion on motor behavioral (e.g., completion time, success rate, cadence, speed, & power), physiological (e.g., heart rate), and psychological (e.g., rated perceived exertion [RPE], intrinsic motivation, & engagement) factors by having participants complete the same stationary cycling task in both a non-immersive and immersive virtual reality environment. Such a comparison allowed for a more direct evaluation regarding how the level of immersion impacted multiple variables associated with the performance of a moderately physically continuous motor skill.

Consistent with previous findings (Juliano & Liew, 2020), the results of the present experiments provide evidence that VR immersion does not differentially impact performance in a comparatively enhancing or depressing manner. Specifically, both experiments showed that overall completion time, speed, cadence, and power did not change based on immersion level (Figure 18). A key performance difference between the two experiments was that success rate, a performance metric specific to the experimental task, did not differ between conditions in experiment two. In experiment one, success rate in the IVR condition was significantly higher when compared to the NIVR condition. These findings were mostly explained by technological limitations (i.e., wireless network instability resulting in lag or skipped frames) in the NIVR condition that were remedied in experiment two, facilitating more accurate performance assessment and comparison across conditions. Altogether, the consistency in the cycling task design and instructions, coupled with the equally game-like design of collecting identical tokens across conditions, likely explains the lack of performance differences found between conditions.

Previous research by Juliano and Liew (2020) similarly found that skill progression occurs at a comparable rate across immersive VR and flat screen environments (i.e., NIVR) when the task design and objective are consistent across platforms. Additionally, Lohse and colleagues (2016) found that gamified environments improve participant speed and accuracy relative to sterile environments. Taken together, these findings suggest that task characteristics may play a more influential role in performance than level of immersion alone. The results of the present study provide further evidence that solely changing the level of immersion is insufficient to differentially impact overall task performance.

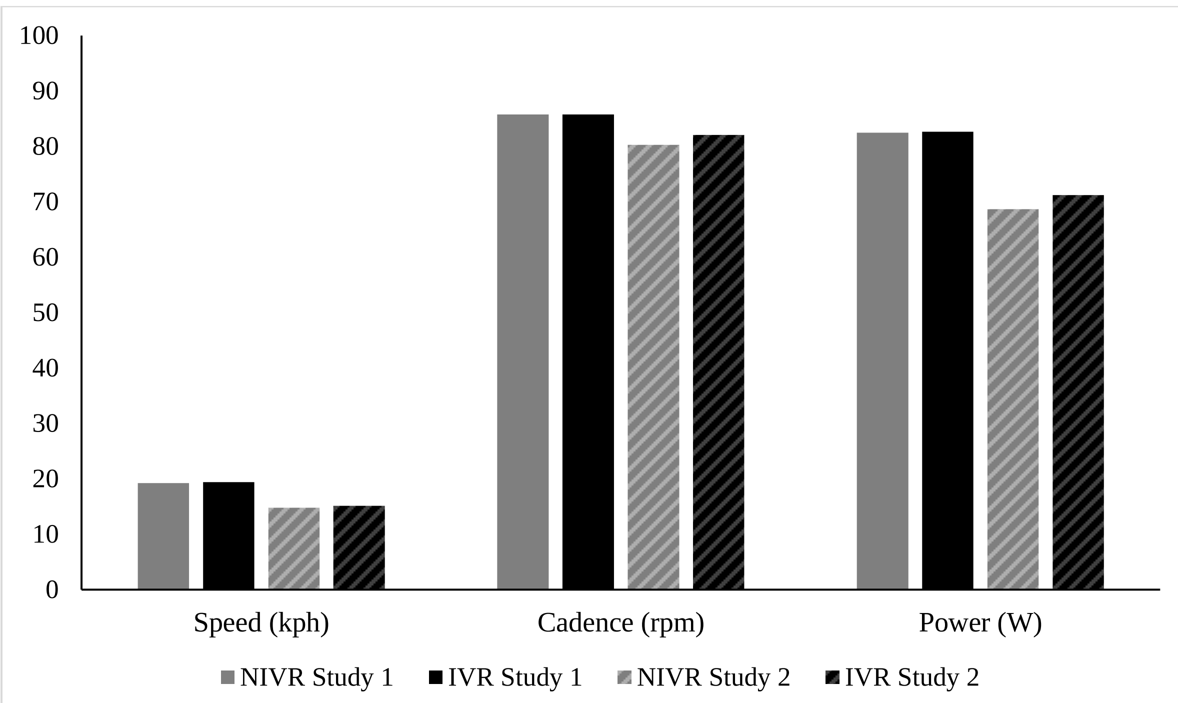

Figure 18. Average speed, cadence, and power for NIVR and IVR conditions in experiments one and two.

In addition to providing evidence that the level of immersion does not impact overall performance of the cycling task utilized in the present study, experiment two revealed meaningful within-task behavioral differences between conditions. During the middle portion of the cycling task, participants temporarily reduced their speed, cadence, and power in the NIVR condition before rising again in the final portion of the task. While the exact cause for this temporary change is unclear, it could be due to sense of presence and perceptions of elapsed time differences (Winter et al., 2021). This conclusion is consistent with findings reported by Bogon and colleagues (2024) which recently found that IVR exclusively altered judgements of time related to physical process duration, and not perceptions of abstract time (i.e., the passage of time). In both experiments of the present dissertation, participants could visually see the distance they had traveled in meters but were blind to how much time had actually elapsed (i.e., abstract time) during the physical performance of the task. However, Bogon and colleagues (2024) findings suggest that the IVR condition could have elicited altered perceptions of how long it took participants to complete a 1000-meter interval (i.e., a physical process associated with traveled distance). While the present dissertation did not include measures of presence or subjective perceptions of time, the behavioral results of experiment two lend further support to this hypothesized conclusion. Specifically, that immersion level may have influenced participant pacing strategies (i.e., how participants distributed their effort and regulated their performance) throughout the task. This was evidenced by condition differences during only the middle portion of the task, despite no impact to their overall task performance. Future studies should include measures of presence and subjective perceptions of time by evaluating how long participants think it took to complete the task to better understand how immersion influences within-task performance variability and pacing strategies.

Consistent with motor behavior measures, both of the present experiments provide evidence that immersion alone does not impact heart rate. These results are incongruent with previous findings that IVR is associated with higher sympathetic nervous system activation

(Malińska et al., 2015), but the findings are congruent with Winter and colleagues' (2021) findings that heart rate did not significantly differ between immersive and non-immersive conditions despite variations in within-task speed. These findings could be due to altered behavioral pacing strategies between conditions, evidenced by the variations in speed, cadence, and power outlined above, rather than changes in physiological workload. Overall, these results suggest differences in physiological responses across levels of immersion may be driven more by behavioral pacing strategies than by the immersion level of the VR environment itself.

Both of the present experiments also provide further evidence that immersion alone does not impact user engagement. Consistent with previous findings (Markwell et al., 2023), both studies of the present dissertation resulted in similar engagement scores across experimental conditions. However, both the present study and Markwell and colleagues' (2023) study utilized a game-like design, which Lohse and colleagues (2016) proposed to be more engaging than sterile environments. Therefore, future studies should investigate these effects in the absence of a game-like design to better understand how task design may impact user engagement in VR and how that constraint may interact with immersion level.

Lastly, previous research has found IVR practice to lead to heightened levels of RPE (Frederikson et al., 2020; Naugle et al., 2024) and intrinsic motivation (Markwell et al., 2023; Polechoński et al., 2024). Consistent with those reported findings, experiment one also demonstrated that IVR practice led to higher levels of RPE and intrinsic motivation compared to NIVR practice. However, experiment two did not show higher intrinsic motivation in the IVR condition, and though RPE was higher on average, it was not statistically significant. The lack of statistical significance in RPE differences may be attributable to the reduced sample size of experiment two resulting in the study being slightly underpowered. However, an explanation for the absence of increased motivation during experiment two is less clear. Previous results (Markwell et al., 2023; Polechoński et al., 2024) combined with the findings from experiment one suggests that IVR environments have the potential to be intrinsically motivating. Specifically, Markwell and colleagues (2023) and experiment one of the present dissertation (Velten, 2024) observed significantly greater global intrinsic motivation in the IVR condition. Although experiment two did not replicate these findings, participants did report higher interest/enjoyment and increased perceived value from pre- to post-test. This time effect may reflect growing feelings of competence, which Self-Determination Theory (Ryan & Deci, 2000) suggests increases with repeated practice and leads to higher intrinsic motivation. Taken together, the incongruent results between studies one and two of the present dissertation warrant future research focused on understanding the specific factors of IVR environments that enhance intrinsic motivation. In line with Self-Determination Theory (Ryan & Deci, 2000), studies including measures of perceived competency may be especially meaningful.

Based on the results of the present dissertation, IVR and NIVR practice environments appear to be equally viable options for practicing motor behavioral skills associated with cycling. Additionally, the results of experiment two suggest these environments may lead to different within-task strategies, such as varying speed or power output throughout the task, even in the absence of cumulative performance differences. Lastly, the combined results of experiments one and two suggest IVR and NIVR environments impact subjective perceptions differently. Specifically, that IVR environments tend to have a greater effect on various psychological variables, including RPE and intrinsic motivation. Altogether, these experiments provide empirical evidence that, when the task demands remain constant, immersion level alone does not significantly impact motor performance or physiological workload but can have an impact on psychological behavior. Researchers and practitioners can utilize these findings to help guide VR practice design. In practical terms, these findings provide meaningful insights for designing effective VR practice with respect to achieving outcome goals, such as improving skill performance, optimizing physical workload, or enhancing psychological affect. Moving forward, many questions surrounding VR practice remain, particularly regarding the transfer of VR learning to RW performance. Those considerations will be discussed in the following sections when the limitations of the dissertation are reviewed and directions for future research are presented.

Limitations

Several limitations should be acknowledged when interpreting the findings of the present dissertation. Although experiment one met the minimum recommended sample size threshold, experiment two fell slightly below the lower end of the recommended minimum sample size range. Although residuals in the analyses for experiment two were normally distributed, this smaller than projected sample size may have made it more difficult to discern smaller effects across the various outcome and performance measures. Additionally, the participants sampled in both experiments consisted of young, healthy, and mostly recreationally physically active adults. Consequently, the results may not generalize to older populations, individuals with lower physical fitness levels, or clinical populations who may experience different balance, motion sensitivity, or attentional demands when practicing in VR.

While the cycling task was intentionally chosen due its highly controlled nature and access to the Wahoo bike, which afforded the opportunity to measure numerous variables associated with the performance of the task, it did not adequately capture the wide range of perceptual, motor, or cognitive decision-making demands representative of more complex motor skills. The present dissertation also did not include a true control condition (e.g., RW or non-gamified condition), so it is unclear if the presented findings were enhancing or depressing relative to those alternative conditions. Lastly, although experiment two added a second day of practice in each condition, the present dissertation focused on immediate performance effects and did not include measures of motor learning or motor skill transfer. Directions for future research that address the limitations acknowledged here are presented in the following section.

Directions for Future Research

Building on the findings of the present dissertation, several suggestions for future research can provide additional clarity and meaningful insights in the relationship between VR immersion and resulting behavioral, physiological, and psychological responses. Firstly, though a number of studies have investigated how VR practice impacts motor skill acquisition (Adamovich et al., 2009; Bhagat et al., 2016; Cevallos et al., 2022; Gray, 2017; Harris et al., 2023; Laver et al., 2017; Liu et al., 2018; Markwell et al., 2023; Michalski et al., 2019b; Oberhauser et al., 2018; Rauter et al., 2013; Sommer et al., 2021; Tirp et al., 2015; Torkington et al., 2001; Wiley et al., 2022), several additional studies did not include measures of motor skill transfer of learning (Cevallos et al., 2022; Harris et al., 2023; Oberhauser et al., 2018; Torkington et al., 2001). The present studies also did not include measures of motor skill transfer, limiting our understanding of how performance in the two VR conditions translates to RW performance. Moving forward, understanding how VR practiced skills transfer to the RW are imperative to utilizing this technology in the most empirical and effective ways. Future studies should incorporate follow-up assessments in the RW to evaluate the extent and direction (i.e., positive or negative) to which skills practiced in VR transfer outside of the virtual environment. Such studies could compare levels of immersion to identify if/how it impacts long term retention and generalization of motor skills. This logical extension of the research presented in this dissertation is imperative for practitioners to better understand how VR may be most effectively used as an alternative or supplement to practicing a task in the real-world.

Another important direction for future research is to evaluate the influence of task design and gamification in VR. Both experiments in the present dissertation utilized a gamified task design, which may have impacted participant engagement and motivation independent of level of immersion. While the present dissertation investigated intrinsic motivation specifically, the role of extrinsic motivation and its relationship with immersion level remains unclear. Previous research suggests that gamified learning contexts satisfy core psychological needs (Ryan & Deci, 2000) through increased intrinsic motivation (Sheldon & Filak, 2008). However, gamified environments also have extrinsic incentives in the form of motivators like points, levels, and leaderboards (Mekler et al., 2017). Therefore, investigating extrinsic motivation in future research may provide meaningful insights regarding how external rewards shape user engagement and effort in VR. It would be beneficial for future studies to investigate how various extrinsic motivators (e.g., points, levels, etc.) interact with immersion to enhance or depress performance and learning effects. It would also be beneficial for future studies to examine the interaction between task design, gamification, and immersion to clarify how these factors influence performance outcomes and the user's subjective experiences. For example, including more sterile, non-gamified tasks or environments could help isolate the effects of immersion and determine how much engagement and motivation are driven by gamified elements.

While the present dissertation purposefully employed a highly controlled motor skill, the cycling task utilized is not representative of the wide range of perceptual, motor, or cognitive decision-making demands of more complex motor skills. Previous research has evaluated a wide range of both open motor skills (Gray, 2017; Michalski et al., 2019b; Rauter et al., 2013) and closed motor skills (Markwell et al., 2023; Tirp et al., 2015; Torkington et al., 2001). However, many of these studies have focused on discrete skills with single actions such as baseball batting (Gray, 2017), golf putting (Markwell et al., 2023), and dart throwing (Tirp et al., 2015). In terms of continuous motor skills, research utilizing fully immersive VR conditions have mainly focused on cycling (e.g., Polechoński et al., 2024; Velten 2024), but one recent review (Dressler & Bachmann, 2025) highlighted several inconsistencies in design and execution across fifty VR cycling studies conducted within the past five years. The present dissertation utilized a standardized protocol for bike fit, but future research should seek to address those inconsistencies by developing additional protocols such as assessing cyclist typology (e.g., Roger Geller test) and implementing familiarization runs. Furthermore, expanding the literature beyond cycling to include a broader range of continuous and complex motor skills, particularly utilizing fully immersive conditions, could provide a more comprehensive understanding of how immersion influences motor performance and cognitive decision-making.

The present dissertation acknowledged homogonous sample characteristics (i.e., young, healthy, and mostly recreationally physically active adults) as a limitation of both the first and second experiments. Previous studies comparing NIVR and IVR conditions have focused mainly on healthy (Kiper et al., 2020; Plechatá et al., 2019; Velten, 2024; Ventura et al., 2019), novice or early learners (Frederikson et al., 2020; Juliano & Liew, 2020; Polechoński et al., 2024). However, it is unclear if and how immersion may impact performers with substantially higher skill level. Therefore, future research should target expert populations to investigate how immersion may impact motor skill refinement and cognitive processing.

Lastly, the results of the present study highlight several minor recommendations for future research as well. Experiment two revealed interesting differences within the middle portion of the cycling task. However, the present dissertation was unable to fully capture the potential mechanisms underlying this effect due to the absence of necessary measurements. Future studies should consider including measures of presence, subjective evaluation of time, and perceptions of competency to better understand how these factors influence performance variability *during* the execution of the practiced task. The inclusion of these measurements would help provide further insight into the cognitive and motivational processes that may be contributing to the within-task performance fluctuations observed in the results of the second experiment included in the present dissertation.

Conclusion

The present dissertation provides a comprehensive investigation into how immersion in VR impacts various behavioral, physiological, and psychological outcomes during a stationary cycling task. Results across the two experiments included in the present dissertation consistently indicated that immersion alone does not significantly impact overall task performance, heart rate variability, or engagement when the task demands and objectives remain constant. Alternatively, the findings of the present dissertation suggest that task design, pacing strategies (i.e., how participants distributed their effort and regulated their performance), and motivational factors play a more influential role in shaping performance within VR environments.

Altogether, these experiments provide empirical evidence that, when the task demands remain constant, immersion level alone does not significantly impact motor performance or physiological workload but may have an impact on psychological responses. Researchers and practitioners can utilize these findings to help guide VR practice design, ensuring design choices target specific outcome goals, such as improving skill performance, optimizing physical and potentially cognitive workload, or enhancing psychological affect.

Beyond research contexts, these findings have meaningful implications for applied settings such as sports coaching, medical training, and military preparation. VR can be used to create or replicate specific skill exercises or decision-making scenarios, but these professionals should not assume immersion alone is enough to increase VR training efficacy. Moreover, based on the results presented here, practitioners should not assume that high levels of immersion are needed to benefit from the utilization of VR in a training or practice environment. Instead, careful attention to task design features is essential to achieving the desired performance and motivational outcomes.

Overall, the present dissertation underscores the importance of a more nuanced, evidence-based approach to VR practice. While level of immersion may have an impact on psychological affect, meaningful differences in performance outcomes are more likely linked to task design elements like gamification. The present dissertation advances both the theoretical understanding and practical guidance of VR training for motor skills and provides a foundation for future research aimed at developing effective, evidence-based VR interventions for diverse populations and applied domains.

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APPENDICES

Appendix A

Motion sickness susceptibility questionnaire short-form (MSSQ-short)

This questionnaire is designed to find out how susceptible to motion sickness you are, and what sorts of motion are most effective in causing that sickness. Sickness here means feeling queasy or nauseated or actually vomiting.

Your childhood experience only (before 12 years of age), for each of the following types of transport or entertainment please indicate

1. **As a child (before age 12),** how often you **felt sick or nauseated** (tick boxes)

	Not Applicable - Never Traveled	Never Felt Sick	Rarely Felt Sick	Sometimes Felt Sick	Frequently Felt Sick
Cars					
Buses or Coaches					
Trains					
Aircraft					
Small Boats					
Ships e.g. Channel Ferries					
Swings in playground					
Roundabouts in playgrounds					
Big Dippers, Funfair Ride					
		0	1	2	3

Your experience over the last 10 years (approximately), for each of the following types of transport or entertainment please indicate

2. **Over the last 10 years**, how often you **felt sick or nauseated** (tick bones)

	Not Applicable - Never Traveled	Never Felt Sick	Rarely Felt Sick	Sometimes Felt Sick	Frequently Felt Sick
Cars					
Buses or Coaches					
Trains					
Aircraft					
Small Boats					
Ships e.g. Channel Ferries					
Swings in playground					
Roundabouts in playgrounds					
Big Dippers, Funfair Ride					
		0	1	2	3

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Appendix B

2019 PAR-Q+

The Physical Activity Readiness Questionnaire for Everyone

The health benefits of regular physical activity are clear; more people should engage in physical activity every day of the week. Participating in physical activity is very safe for MOST people. This questionnaire will tell you whether it is necessary for you to seek further advice from your doctor OR a qualified exercise professional before becoming more physically active.

GENERAL HEALTH QUESTIONS

Please read the 7 questions below carefully and answer each one honestly: check YES or NO.	YES	NO
1) Has your doctor ever said that you have a heart condition ☐ OR high blood pressure ☐?	☐	☐
2) Do you feel pain in your chest at rest, during your daily activities of living, **OR** when you do physical activity?	☐	☐
3) Do you lose balance because of dizziness **OR** have you lost consciousness in the last 12 months? Please answer **NO** if your dizziness was associated with over-breathing (including during vigorous exercise).	☐	☐
4) Have you ever been diagnosed with another chronic medical condition (other than heart disease or high blood pressure)? **PLEASE LIST CONDITION(S) HERE:** ______________________	☐	☐
5) Are you currently taking prescribed medications for a chronic medical condition? **PLEASE LIST CONDITION(S) AND MEDICATIONS HERE:** ______________________	☐	☐
6) Do you currently have (or have had within the past 12 months) a bone, joint, or soft tissue (muscle, ligament, or tendon) problem that could be made worse by becoming more physically active? Please answer **NO** if you had a problem in the past, but it **does not limit your current ability** to be physically active. **PLEASE LIST CONDITION(S) HERE:** ______________________	☐	☐
7) Has your doctor ever said that you should only do medically supervised physical activity?	☐	☐

If you answered NO to all of the questions above, you are cleared for physical activity.
Please sign the PARTICIPANT DECLARATION. You do not need to complete Pages 2 and 3.

- Start becoming much more physically active – start slowly and build up gradually.
- Follow International Physical Activity Guidelines for your age (www.who.int/dietphysicalactivity/en/).
- You may take part in a health and fitness appraisal.
- If you are over the age of 45 yr and NOT accustomed to regular vigorous to maximal effort exercise, consult a qualified exercise professional before engaging in this intensity of exercise.
- If you have any further questions, contact a qualified exercise professional.

PARTICIPANT DECLARATION
If you are less than the legal age required for consent or require the assent of a care provider, your parent, guardian or care provider must also sign this form.

I, the undersigned, have read, understood to my full satisfaction and completed this questionnaire. I acknowledge that this physical activity clearance is valid for a maximum of 12 months from the date it is completed and becomes invalid if my condition changes. I also acknowledge that the community/fitness center may retain a copy of this form for its records. In these instances, it will maintain the confidentiality of the same, complying with applicable law.

NAME ______________________________ DATE ______________

SIGNATURE ______________________________ WITNESS ______________

SIGNATURE OF PARENT/GUARDIAN/CARE PROVIDER ______________________________

If you answered YES to one or more of the questions above, COMPLETE PAGES 2 AND 3.

Delay becoming more active if:

- You have a temporary illness such as a cold or fever; it is best to wait until you feel better.
- You are pregnant - talk to your health care practitioner, your physician, a qualified exercise professional, and/or complete the ePARmed-X+ at **www.eparmedx.com** before becoming more physically active.
- Your health changes - answer the questions on Pages 2 and 3 of this document and/or talk to your doctor or a qualified exercise professional before continuing with any physical activity program.

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Appendix C

Intrinsic Motivation Inventory (IMI)

For each of the following statements, please indicate how true it is for you, using the following scale:

1	2	3	4	5	6	7
Not at all true			Somewhat true			Very true

Interest/Enjoyment

I enjoyed doing this activity very much.
This activity was fun to do.
I thought this was a boring activity.
This activity did not hold my attention at all.
I would describe this activity as very interesting.
I thought this activity was quite enjoyable.
While I was doing this activity, I was thinking about how much I enjoyed it.

Perceived Competence

I think I am pretty good at this activity.
I think I did pretty well at this activity, compared to other participants.
After working at this activity for a while, I felt pretty competent.
I am satisfied with my performance at this task.
I was pretty skilled at this activity.
This was an activity that I couldn’t do very well. (R)

Effort/Importance

I put a lot of effort into this.
I didn’t try very hard to do well at this activity. (R)
I tried very hard on this activity.
It was important to me to do well at this task.
I didn’t put much energy into this. (R)

Pressure/Tension

I did not feel nervous at all while doing this (R)
I felt very tense while doing this activity.
I was very relaxed while doing this. (R)
I was anxious while working on this task.

I felt pressured while doing this.

Perceived Choice

I believe I had some choice about doing this activity.
I felt like it was not my own choice to do this task. (R)
I didn't really have a choice about doing this task. (R)
I felt like I had to do this. (R)
I did this activity because I had no choice. (R)
I did this activity because I wanted to.
I did this activity because I had to. (R)

Value/Usefulness

I believe this activity could be of some value to me.
I think that doing this activity is useful for improving stationary cycling performance.
I think this is important to do because it can improve my stationary cycling ability.
I would be willing to do this again because it has some value to me.
I think doing this activity could help me to improve my stationary cycling ability.
I believe doing this activity could be beneficial to me.
I think this is an important activity.

Appendix D

Engagement Scale questions

Modified from (Agbuga et al., 2015; Jang, Reeve, & Deci, 2010)

1		2		3		4		5
Strongly Disagree				Neither Agree nor Disagree				Strongly Agree

"While I was performing the task during the practice sessions…"

Behavioral Engagement

I paid attention

I worked very hard

I tried to do well

Cognitive Engagement

I tried to master the task as much as I could

I tried to focus my attention on performing the task well

Emotional Engagement

I enjoyed the practice session

I felt interested in learning the task

Appendix E

Verbal Instructions

"In a moment, you will complete a cycling task. You will be cycling down a road and Power Ts will randomly generate in front of you. To collect a Power T, all you need to do is ride through it. The bike tempo is matched to you – meaning if you pedal faster, you'll move faster; if you pedal slower, you'll move slower. To switch lanes, use the buttons on the inside of the handlebars. The course is at a fixed distance of 8000 meters. The course will automatically end when you've reached the finish line, so keep pedaling until the save screen pops up. We will be tracking how many Power Ts you collect and how fast you complete the ride."

Appendix F

Experiment Two Statistical Output

Comparing Day 1 and 2 for Carryover

RPE

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	18.550	282.147	<.001
Condition	1	18.550	2.304	.146
Laps	7	119.987	22.274	<.001
rep	1	19.984	3.896	.062
Condition * Laps	7	119.987	.464	.859
Condition * rep	1	19.984	.185	.672
Laps * rep	7	119.570	.831	.563
Condition * Laps * rep	7	119.570	.642	.720

a. Dependent Variable: RPE.

Estimated Marginal Means

1. Condition[a]

Condition	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	4.743	.461	18.579	3.776	5.710
2	5.685	.415	18.507	4.814	6.557

a. Dependent Variable: RPE.

2. Laps[a]

Laps	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	3.465	.336	25.810	2.774	4.155
2	4.346	.337	25.798	3.654	5.038
3	4.818	.337	25.781	4.125	5.511
4	5.162	.337	25.755	4.468	5.855
5	5.551	.337	25.716	4.857	6.244
6	5.790	.337	25.848	5.097	6.484
7	5.968	.337	25.941	5.274	6.661
8	6.615	.337	26.006	5.923	7.307

a. Dependent Variable: RPE.

3. rep[a]

rep	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1.00	5.437	.335	23.899	4.744	6.129
2.00	4.992	.325	22.823	4.319	5.665

a. Dependent Variable: RPE.

4. Condition * Laps[a]

Condition	Laps	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1	3.111	.499	25.838	2.085	4.137
	2	4.056	.500	25.838	3.027	5.084
	3	4.500	.501	25.838	3.470	5.530
	4	4.778	.501	25.838	3.747	5.808
	5	5.056	.501	25.838	4.025	6.086
	6	5.167	.501	25.838	4.137	6.196
	7	5.278	.500	25.838	4.250	6.306
	8	6.000	.499	25.838	4.974	7.026
2	1	3.818	.450	25.775	2.893	4.743
	2	4.636	.451	25.746	3.710	5.563
	3	5.136	.451	25.703	4.209	6.064
	4	5.545	.451	25.639	4.617	6.474
	5	6.045	.451	25.540	5.117	6.973
	6	6.414	.452	25.825	5.484	7.343
	7	6.657	.452	26.045	5.728	7.587
	8	7.230	.452	26.197	6.301	8.159

a. Dependent Variable: RPE.

5. Condition * rep[a]

Condition	rep	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1.00	5.014	.498	23.968	3.986	6.042
	2.00	4.472	.483	22.837	3.472	5.472
2	1.00	5.859	.449	23.776	4.932	6.787
	2.00	5.511	.435	22.805	4.611	6.412

a. Dependent Variable: RPE.

6. Laps * rep[a]

Laps	rep	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1.00	3.566	.371	34.442	2.812	4.319
	2.00	3.364	.357	33.256	2.639	4.089
2	1.00	4.530	.372	34.395	3.776	5.285
	2.00	4.162	.357	33.254	3.435	4.888
3	1.00	5.116	.372	34.325	4.361	5.872
	2.00	4.520	.358	33.251	3.793	5.248
4	1.00	5.465	.372	34.222	4.709	6.221
	2.00	4.859	.358	33.246	4.131	5.586
5	1.00	5.803	.372	34.068	5.047	6.559
	2.00	5.298	.358	33.240	4.570	6.026
6	1.00	5.954	.373	34.537	5.196	6.712
	2.00	5.626	.358	33.221	4.899	6.354
7	1.00	6.162	.374	34.873	5.404	6.921
	2.00	5.773	.357	33.218	5.046	6.499
8	1.00	6.897	.374	35.098	6.138	7.655
	2.00	6.333	.357	33.216	5.608	7.059

a. Dependent Variable: RPE.

7. Condition * Laps * rep[a]

Condition	Laps	rep	Mean	Std. Error	df	95% Confidence Interval	
						Lower Bound	Upper Bound
1	1	1.00	3.222	.551	34.548	2.103	4.341
		2.00	3.000	.530	33.261	1.923	4.077
	2	1.00	4.333	.552	34.548	3.213	5.454
		2.00	3.778	.531	33.261	2.698	4.857
	3	1.00	4.778	.553	34.548	3.656	5.900
		2.00	4.222	.531	33.261	3.141	5.303
	4	1.00	5.111	.553	34.548	3.988	6.234
		2.00	4.444	.532	33.261	3.363	5.526
	5	1.00	5.333	.553	34.548	4.210	6.456
		2.00	4.778	.532	33.261	3.696	5.859
	6	1.00	5.444	.553	34.548	4.322	6.567
		2.00	4.889	.531	33.261	3.808	5.970
	7	1.00	5.556	.552	34.548	4.435	6.676
		2.00	5.000	.531	33.261	3.921	6.079
	8	1.00	6.333	.551	34.548	5.215	7.452
		2.00	5.667	.530	33.261	4.589	6.744
2	1	1.00	3.909	.497	34.303	2.900	4.918
		2.00	3.727	.477	33.250	2.756	4.698
	2	1.00	4.727	.498	34.189	3.716	5.738
		2.00	4.545	.478	33.245	3.573	5.518
	3	1.00	5.455	.498	34.017	4.443	6.467
		2.00	4.818	.479	33.238	3.844	5.792
	4	1.00	5.818	.498	33.753	4.806	6.831
		2.00	5.273	.479	33.227	4.298	6.247
	5	1.00	6.273	.498	33.341	5.261	7.285
		2.00	5.818	.479	33.211	4.844	6.792
	6	1.00	6.464	.502	34.386	5.445	7.483
		2.00	6.364	.479	33.162	5.390	7.337
	7	1.00	6.769	.504	35.176	5.746	7.792
		2.00	6.545	.478	33.159	5.573	7.518
	8	1.00	7.460	.505	35.706	6.435	8.485
		2.00	7.000	.477	33.155	6.029	7.971

a. Dependent Variable: RPE.

Success Rate

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	18.696	11662.474	<.001
Condition	1	18.696	3.920	.063
Laps	7	111.802	.520	.818
rep	1	74.540	.001	.982
Condition * Laps	7	111.802	1.361	.229
Condition * rep	1	74.540	.193	.662
Laps * rep	7	124.868	1.228	.292
Condition * Laps * rep	7	124.868	1.253	.279

a. Dependent Variable: Success Rate.

Estimated Marginal Means

1. Condition[a]

Condition	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1	.534	.007	18.165	.519	.550
2	.554	.007	19.341	.540	.569

a. Dependent Variable: Success Rate.

2. Laps[a]

Laps	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1	.548	.010	130.830	.527	.568
2	.545	.010	130.830	.524	.565
3	.543	.010	130.830	.523	.563
4	.558	.010	130.830	.538	.579
5	.546	.010	130.830	.526	.566
6	.536	.010	130.830	.516	.557
7	.541	.010	130.830	.521	.561
8	.539	.010	130.830	.518	.559

a. Dependent Variable: Success Rate.

3. rep[a]

rep	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1.00	.545	.006	26.345	.533	.556
2.00	.544	.006	36.201	.532	.557

a. Dependent Variable: Success Rate.

4. Condition * Laps[a]

Condition	Laps	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1	.542	.015	125.681	.513	.572
	2	.527	.015	125.681	.497	.557
	3	.517	.015	125.681	.488	.547
	4	.536	.015	125.681	.506	.565
	5	.549	.015	125.681	.519	.578
	6	.526	.015	125.681	.497	.556
	7	.539	.015	125.681	.509	.569
	8	.539	.015	125.681	.510	.569
2	1	.553	.014	136.773	.525	.581
	2	.563	.014	136.773	.535	.590
	3	.569	.014	136.773	.541	.597
	4	.581	.014	136.773	.553	.609
	5	.543	.014	136.773	.515	.571
	6	.546	.014	136.773	.519	.574
	7	.543	.014	136.773	.515	.571
	8	.538	.014	136.773	.510	.565

a. Dependent Variable: Success Rate.

5. Condition * rep[a]

Condition	rep	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1.00	.533	.008	24.456	.517	.550
	2.00	.536	.009	36.216	.518	.554
2	1.00	.556	.008	28.518	.540	.572
	2.00	.553	.008	36.183	.537	.570

a. Dependent Variable: Success Rate.

6. Laps * rep[a]

Laps	rep	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1.00	.546	.012	123.738	.521	.571
	2.00	.549	.014	143.760	.521	.577
2	1.00	.544	.013	123.738	.519	.569
	2.00	.545	.014	143.760	.517	.573
3	1.00	.522	.013	123.738	.497	.547
	2.00	.564	.014	143.760	.536	.592
4	1.00	.558	.013	123.738	.534	.583
	2.00	.559	.014	143.760	.531	.587
5	1.00	.553	.013	123.738	.528	.577
	2.00	.539	.014	143.760	.511	.567
6	1.00	.541	.013	123.738	.516	.565
	2.00	.532	.014	143.760	.504	.560
7	1.00	.551	.013	123.738	.526	.576
	2.00	.531	.014	143.760	.503	.559
8	1.00	.542	.012	123.738	.517	.566
	2.00	.535	.014	143.760	.507	.563

a. Dependent Variable: Success Rate.

7. Condition * Laps * rep[a]

Condition	Laps	rep	Mean	Std. Error	df	95% Confidence Interval	
						Lower Bound	Upper Bound
1	1	1.00	.536	.018	121.850	.501	.571
		2.00	.549	.021	144.327	.508	.591
	2	1.00	.535	.018	121.850	.499	.570
		2.00	.520	.021	144.327	.478	.561
	3	1.00	.477	.018	121.850	.442	.512
		2.00	.557	.021	144.327	.516	.599
	4	1.00	.550	.018	121.850	.515	.585
		2.00	.522	.021	144.327	.480	.563
	5	1.00	.552	.018	121.850	.517	.587
		2.00	.545	.021	144.327	.504	.587
	6	1.00	.531	.018	121.850	.496	.566
		2.00	.522	.021	144.327	.480	.563
	7	1.00	.544	.018	121.850	.509	.579
		2.00	.534	.021	144.327	.492	.575
	8	1.00	.542	.018	121.850	.507	.577
		2.00	.537	.021	144.327	.496	.579
2	1	1.00	.556	.018	125.467	.522	.591
		2.00	.550	.019	143.071	.512	.587
	2	1.00	.554	.018	125.467	.519	.589
		2.00	.571	.019	143.071	.534	.609
	3	1.00	.567	.018	125.467	.532	.602
		2.00	.571	.019	143.071	.533	.608
	4	1.00	.567	.018	125.467	.532	.602
		2.00	.595	.019	143.071	.558	.633
	5	1.00	.553	.018	125.467	.518	.588
		2.00	.534	.019	143.071	.496	.571
	6	1.00	.550	.018	125.467	.515	.585
		2.00	.543	.019	143.071	.505	.580
	7	1.00	.558	.018	125.467	.523	.593
		2.00	.528	.019	143.071	.490	.565
	8	1.00	.541	.018	125.467	.507	.576
		2.00	.534	.019	143.071	.496	.571

a. Dependent Variable: Success Rate.

Heart Rate

Warnings

Iteration was terminated but convergence has not been achieved. The MIXED procedure continues despite this warning. Subsequent results produced are based on the last iteration. Validity of the model fit is uncertain.

Fixed Effects

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	17.045	1110.703	<.001
Condition	1	17.045	.288	.598
Laps	7	120.481	45.660	<.001
rep	1	14.863	2.497	.135
Condition * Laps	7	120.481	1.698	.116
Condition * rep	1	14.863	.232	.637
Laps * rep	7	129.194	.669	.698
Condition * Laps * rep	7	129.194	1.181	.318

a. Dependent Variable: HR (bpm).

Estimated Marginal Means

1. Condition[a]

Condition	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1	135.681	5.928	16.839	123.164	148.197
2	131.378	5.392	17.298	120.017	142.739

a. Dependent Variable: HR (bpm).

2. Laps[a]

Laps	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1	113.579	4.134	19.435	104.938	122.219
2	128.489	4.139	19.435	119.839	137.140
3	132.911	4.143	19.435	124.253	141.568
4	134.505	4.144	19.435	125.844	143.165
5	136.640	4.144	19.435	127.979	145.301
6	138.256	4.143	19.435	129.599	146.914
7	140.010	4.139	19.435	131.359	148.660
8	143.845	4.134	19.435	135.204	152.485

a. Dependent Variable: HR (bpm).

3. rep[a]

rep	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1.00	130.971	4.300	22.838	122.072	139.871
2.00	136.087	4.342	24.351	127.132	145.042

a. Dependent Variable: HR (bpm).

4. Condition * Laps[a]

Condition	Laps	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1	113.667	6.114	19.172	100.877	126.456
	2	131.333	6.122	19.172	118.529	144.138
	3	135.111	6.127	19.172	122.296	147.926
	4	136.333	6.129	19.172	123.513	149.154
	5	138.500	6.129	19.172	125.680	151.320
	6	140.000	6.127	19.172	127.185	152.815
	7	142.556	6.122	19.172	129.751	155.360
	8	147.944	6.114	19.172	135.155	160.734
2	1	113.491	5.567	19.758	101.869	125.112
	2	125.645	5.573	19.758	114.010	137.280
	3	130.710	5.578	19.758	119.066	142.354
	4	132.676	5.580	19.758	121.027	144.324
	5	134.780	5.580	19.758	123.132	146.429
	6	136.512	5.578	19.758	124.868	148.156
	7	137.463	5.573	19.758	125.829	149.098
	8	139.745	5.567	19.758	128.123	151.366

a. Dependent Variable: HR (bpm).

5. Condition * rep[a]

Condition	rep	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1.00	133.903	6.305	22.082	120.830	146.976
	2.00	137.458	6.450	24.352	124.157	150.760
2	1.00	128.040	5.850	23.735	115.959	140.121
	2.00	134.716	5.815	24.349	122.723	146.709

a. Dependent Variable: HR (bpm).

6. Laps * rep[a]

Laps	rep	Mean	Std. Error	df	95% Confidence Interval	
					Lower Bound	Upper Bound
1	1.00	109.799	4.512	27.329	100.546	119.052
	2.00	117.359	4.568	29.654	108.025	126.693
2	1.00	124.655	4.517	27.329	115.393	133.918
	2.00	132.323	4.573	29.654	122.980	141.666
3	1.00	129.069	4.520	27.329	119.800	138.338
	2.00	136.753	4.575	29.654	127.404	146.102
4	1.00	130.994	4.521	27.329	121.722	140.266
	2.00	138.015	4.577	29.654	128.663	147.367
5	1.00	134.876	4.521	27.329	125.604	144.148
	2.00	138.404	4.577	29.654	129.052	147.756
6	1.00	136.775	4.520	27.329	127.506	146.044
	2.00	139.737	4.575	29.654	130.388	149.086
7	1.00	138.706	4.517	27.329	129.443	147.969
	2.00	141.313	4.573	29.654	131.970	150.656
8	1.00	142.896	4.512	27.329	133.643	152.149
	2.00	144.793	4.568	29.654	135.459	154.127

a. Dependent Variable: HR (bpm).

7. Condition * Laps * rep[a]

Condition	Laps	rep	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1	1.00	112.889	6.609	26.351	99.313	126.465
		2.00	114.444	6.784	29.656	100.583	128.306
	2	1.00	128.111	6.616	26.351	114.521	141.701
		2.00	134.556	6.791	29.656	120.680	148.431
	3	1.00	131.444	6.620	26.351	117.845	145.044
		2.00	138.778	6.796	29.656	124.893	152.663
	4	1.00	133.000	6.623	26.351	119.396	146.604
		2.00	139.667	6.798	29.656	125.777	153.556
	5	1.00	137.556	6.623	26.351	123.951	151.160
		2.00	139.444	6.798	29.656	125.555	153.334
	6	1.00	138.889	6.620	26.351	125.289	152.489
		2.00	141.111	6.796	29.656	127.226	154.996
	7	1.00	141.667	6.616	26.351	128.076	155.257
		2.00	143.444	6.791	29.656	129.569	157.320
	8	1.00	147.667	6.609	26.351	134.090	161.243
		2.00	148.222	6.784	29.656	134.360	162.084
2	1	1.00	106.709	6.145	28.492	94.131	119.287
		2.00	120.273	6.119	29.651	107.769	132.776
	2	1.00	121.199	6.151	28.492	108.609	133.790
		2.00	130.091	6.125	29.651	117.576	142.606
	3	1.00	126.694	6.155	28.492	114.095	139.293
		2.00	134.727	6.129	29.651	122.204	147.250
	4	1.00	128.988	6.157	28.492	116.385	141.591
		2.00	136.364	6.131	29.651	123.837	148.890
	5	1.00	132.197	6.157	28.492	119.594	144.800
		2.00	137.364	6.131	29.651	124.837	149.890
	6	1.00	134.661	6.155	28.492	122.062	147.260
		2.00	138.364	6.129	29.651	125.841	150.886
	7	1.00	135.745	6.151	28.492	123.154	148.336
		2.00	139.182	6.125	29.651	126.667	151.697
	8	1.00	138.126	6.145	28.492	125.548	150.704
		2.00	141.364	6.119	29.651	128.860	153.867

a. Dependent Variable: HR (bpm).

Speed

Warnings

Iteration was terminated but convergence has not been achieved. The MIXED procedure continues despite this warning. Subsequent results produced are based on the last iteration. Validity of the model fit is uncertain.

Fixed Effects

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	18.329	818.372	<.001
Condition	1	18.329	.104	.750
Laps	7	123.590	8.375	<.001
rep	1	14.050	.238	.633
Condition * Laps	7	123.590	3.072	.005
Condition * rep	1	14.050	.038	.848
Laps * rep	7	120.002	2.191	.040
Condition * Laps * rep	7	120.002	.830	.565

a. Dependent Variable: Speed (mph).

Estimated Marginal Means

1. Condition[a]

Condition	Mean	Std. Error	df	95% Confidence Interval Lower Bound	Upper Bound
1	9.498	.486	18.165	8.477	10.519
2	9.286	.441	18.529	8.361	10.211

a. Dependent Variable: Speed (mph).

2. Laps[a]

Laps	Mean	Std. Error	df	95% Confidence Interval Lower Bound	Upper Bound
1	8.975	.335	19.771	8.276	9.674
2	9.279	.335	19.771	8.580	9.979
3	9.361	.335	19.771	8.661	10.060
4	9.362	.335	19.771	8.662	10.061
5	9.398	.335	19.771	8.699	10.098
6	9.399	.335	19.771	8.700	10.099
7	9.540	.335	19.771	8.840	10.239
8	9.821	.335	19.771	9.122	10.519

a. Dependent Variable: Speed (mph).

3. rep[a]

rep	Mean	Std. Error	df	95% Confidence Interval Lower Bound	Upper Bound
1.00	9.340	.355	24.264	8.607	10.072
2.00	9.444	.335	20.096	8.745	10.143

a. Dependent Variable: Speed (mph).

4. Condition * Laps[a]

Condition	Laps	Mean	Std. Error	df	95% Confidence Interval	
					Lower Bound	Upper Bound
1	1	9.333	.496	19.573	8.298	10.369
	2	9.472	.496	19.573	8.436	10.508
	3	9.383	.496	19.573	8.347	10.420
	4	9.344	.496	19.573	8.308	10.381
	5	9.406	.496	19.573	8.369	10.442
	6	9.400	.496	19.573	8.364	10.436
	7	9.617	.496	19.573	8.581	10.653
	8	10.028	.496	19.573	8.992	11.063
2	1	8.617	.450	20.012	7.678	9.556
	2	9.087	.450	20.012	8.147	10.026
	3	9.338	.450	20.012	8.399	10.278
	4	9.379	.451	20.012	8.439	10.319
	5	9.391	.451	20.012	8.452	10.331
	6	9.398	.450	20.012	8.459	10.338
	7	9.462	.450	20.012	8.523	10.402
	8	9.613	.450	20.012	8.675	10.552

a. Dependent Variable: Speed (mph).

5. Condition * rep[a]

Condition	rep	Mean	Std. Error	df	95% Confidence Interval	
					Lower Bound	Upper Bound
1	1.00	9.425	.523	23.739	8.346	10.504
	2.00	9.571	.498	20.098	8.533	10.609
2	1.00	9.254	.481	24.879	8.264	10.245
	2.00	9.317	.449	20.094	8.381	10.253

a. Dependent Variable: Speed (mph).

6. Laps * rep[a]

Laps	rep	Mean	Std. Error	df	95% Confidence Interval	
					Lower Bound	Upper Bound
1	1.00	8.815	.367	27.271	8.063	9.568
	2.00	9.135	.343	22.000	8.424	9.846
2	1.00	9.077	.367	27.271	8.324	9.830
	2.00	9.482	.343	22.000	8.770	10.193
3	1.00	9.159	.367	27.271	8.406	9.913
	2.00	9.562	.343	22.000	8.850	10.274
4	1.00	9.276	.367	27.271	8.523	10.030
	2.00	9.447	.343	22.000	8.735	10.159
5	1.00	9.419	.367	27.271	8.665	10.172
	2.00	9.378	.343	22.000	8.667	10.090
6	1.00	9.456	.367	27.271	8.703	10.209
	2.00	9.342	.343	22.000	8.631	10.054
7	1.00	9.583	.367	27.271	8.830	10.336
	2.00	9.496	.343	22.000	8.785	10.208
8	1.00	9.933	.367	27.271	9.180	10.685
	2.00	9.709	.343	22.000	8.998	10.420

a. Dependent Variable: Speed (mph).

7. Condition * Laps * rep[a]

Condition	Laps	rep	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1	1.00	9.133	.540	26.615	8.025	10.241
		2.00	9.533	.509	22.003	8.477	10.589
	2	1.00	9.244	.540	26.615	8.136	10.353
		2.00	9.700	.510	22.003	8.643	10.757
	3	1.00	9.133	.540	26.615	8.024	10.242
		2.00	9.633	.510	22.003	8.576	10.690
	4	1.00	9.222	.540	26.615	8.113	10.331
		2.00	9.467	.510	22.003	8.409	10.524
	5	1.00	9.400	.540	26.615	8.291	10.509
		2.00	9.411	.510	22.003	8.354	10.468
	6	1.00	9.433	.540	26.615	8.324	10.542
		2.00	9.367	.510	22.003	8.310	10.424
	7	1.00	9.622	.540	26.615	8.514	10.731
		2.00	9.611	.510	22.003	8.554	10.668
	8	1.00	10.211	.540	26.615	9.103	11.319
		2.00	9.844	.509	22.003	8.788	10.900
2	1	1.00	8.498	.497	28.044	7.479	9.517
		2.00	8.736	.459	21.996	7.784	9.689
	2	1.00	8.909	.498	28.044	7.890	9.929
		2.00	9.264	.459	21.996	8.311	10.216
	3	1.00	9.185	.498	28.044	8.166	10.205
		2.00	9.491	.460	21.996	8.538	10.444
	4	1.00	9.331	.498	28.044	8.311	10.350
		2.00	9.427	.460	21.996	8.474	10.380
	5	1.00	9.437	.498	28.044	8.418	10.457
		2.00	9.345	.460	21.996	8.392	10.299
	6	1.00	9.478	.498	28.044	8.459	10.498
		2.00	9.318	.460	21.996	8.365	10.271
	7	1.00	9.543	.498	28.044	8.524	10.562
		2.00	9.382	.459	21.996	8.429	10.335
	8	1.00	9.654	.497	28.044	8.635	10.673
		2.00	9.573	.459	21.996	8.621	10.525

a. Dependent Variable: Speed (mph).

Cadence

Warnings

Iteration was terminated but convergence has not been achieved. The MIXED procedure continues despite this warning. Subsequent results produced are based on the last iteration. Validity of the model fit is uncertain.

Fixed Effects

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	18.241	824.325	<.001
Condition	1	18.241	.136	.717
Laps	7	121.987	6.917	<.001
rep	1	13.975	.340	.569
Condition * Laps	7	121.987	3.910	<.001
Condition * rep	1	13.975	.003	.957
Laps * rep	7	119.211	1.827	.088
Condition * Laps * rep	7	119.211	.929	.486

a. Dependent Variable: Cadence (rpm).

Estimated Marginal Means

1. Condition[a]

Condition	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1	83.042	4.230	18.092	74.157	91.926
2	80.937	3.837	18.422	72.889	88.986

a. Dependent Variable: Cadence (rpm).

2. Laps[a]

Laps	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1	78.999	2.907	19.564	72.925	85.072
2	81.107	2.909	19.564	75.030	87.184
3	81.640	2.910	19.564	75.560	87.719
4	81.545	2.911	19.564	75.464	87.625
5	81.873	2.911	19.564	75.793	87.954
6	82.039	2.910	19.564	75.960	88.118
7	83.209	2.909	19.564	77.132	89.286
8	85.505	2.907	19.564	79.431	91.578

a. Dependent Variable: Cadence (rpm).

3. rep[a]

rep	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1.00	81.469	3.064	23.550	75.139	87.799
2.00	82.510	2.918	20.053	76.424	88.596

a. Dependent Variable: Cadence (rpm).

4. Condition * Laps[a]

Condition	Laps	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1	82.389	4.305	19.384	73.390	91.388
	2	82.722	4.308	19.384	73.718	91.727
	3	81.833	4.310	19.384	72.825	90.842
	4	81.500	4.311	19.384	72.490	90.510
	5	82.000	4.311	19.384	72.990	91.010
	6	82.167	4.310	19.384	73.158	91.175
	7	84.111	4.308	19.384	75.106	93.116
	8	87.611	4.305	19.384	78.612	96.610
2	1	75.609	3.908	19.783	67.450	83.767
	2	79.492	3.911	19.783	71.329	87.655
	3	81.446	3.912	19.783	73.280	89.612
	4	81.589	3.913	19.783	73.422	89.757
	5	81.747	3.913	19.783	73.579	89.914
	6	81.912	3.912	19.783	73.746	90.078
	7	82.307	3.911	19.783	74.144	90.470
	8	83.399	3.908	19.783	75.240	91.557

a. Dependent Variable: Cadence (rpm).

5. Condition * rep[a]

Condition	rep	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1.00	82.472	4.512	23.053	73.140	91.805
	2.00	83.611	4.334	20.054	74.573	92.649
2	1.00	80.466	4.147	24.137	71.910	89.022
	2.00	81.409	3.908	20.051	73.258	89.561

a. Dependent Variable: Cadence (rpm).

6. Laps * rep[a]

Laps	rep	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1.00	77.679	3.160	26.307	71.187	84.172
	2.00	80.318	2.983	21.861	74.129	86.507
2	1.00	79.437	3.162	26.307	72.941	85.932
	2.00	82.778	2.985	21.861	76.586	88.970
3	1.00	79.915	3.163	26.307	73.418	86.413
	2.00	83.364	2.986	21.861	77.169	89.558
4	1.00	80.731	3.163	26.307	74.232	87.229
	2.00	82.359	2.986	21.861	76.163	88.554
5	1.00	81.838	3.163	26.307	75.339	88.337
	2.00	81.909	2.986	21.861	75.714	88.105
6	1.00	82.397	3.163	26.307	75.899	88.894
	2.00	81.682	2.986	21.861	75.487	87.876
7	1.00	83.473	3.162	26.307	76.978	89.969
	2.00	82.944	2.985	21.861	76.752	89.137
8	1.00	86.283	3.160	26.307	79.790	92.775
	2.00	84.727	2.983	21.861	78.538	90.916

a. Dependent Variable: Cadence (rpm).

7. Condition * Laps * rep[a]

Condition	Laps	rep	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1	1.00	80.778	4.650	25.687	71.214	90.341
		2.00	84.000	4.430	21.864	74.809	93.191
	2	1.00	80.889	4.652	25.687	71.321	90.457
		2.00	84.556	4.433	21.864	75.359	93.752
	3	1.00	79.667	4.654	25.687	70.095	89.238
		2.00	84.000	4.434	21.864	74.800	93.200
	4	1.00	80.556	4.654	25.687	70.982	90.129
		2.00	82.444	4.435	21.864	73.243	91.646
	5	1.00	82.000	4.654	25.687	72.427	91.573
		2.00	82.000	4.435	21.864	72.799	91.201
	6	1.00	82.333	4.654	25.687	72.762	91.905
		2.00	82.000	4.434	21.864	72.800	91.200
	7	1.00	84.333	4.652	25.687	74.765	93.902
		2.00	83.889	4.433	21.864	74.693	93.085
	8	1.00	89.222	4.650	25.687	79.659	98.786
		2.00	86.000	4.430	21.864	76.809	95.191
2	1	1.00	74.581	4.281	27.043	65.797	83.365
		2.00	76.636	3.996	21.858	68.346	84.927
	2	1.00	77.985	4.283	27.043	69.197	86.773
		2.00	81.000	3.998	21.858	72.705	89.295
	3	1.00	80.164	4.285	27.043	71.373	88.955
		2.00	82.727	4.000	21.858	74.430	91.025
	4	1.00	80.906	4.285	27.043	72.113	89.698
		2.00	82.273	4.000	21.858	73.974	90.572
	5	1.00	81.676	4.285	27.043	72.883	90.468
		2.00	81.818	4.000	21.858	73.519	90.117
	6	1.00	82.460	4.285	27.043	73.669	91.251
		2.00	81.364	4.000	21.858	73.066	89.661
	7	1.00	82.613	4.283	27.043	73.825	91.401
		2.00	82.000	3.998	21.858	73.705	90.295
	8	1.00	83.343	4.281	27.043	74.559	92.127
		2.00	83.455	3.996	21.858	75.164	91.745

a. Dependent Variable: Cadence (rpm).

Power

Fixed Effects

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	18.979	306.911	<.001
Condition	1	18.979	.084	.775
Laps	7	120.799	7.011	<.001
rep	1	16.561	.621	.442
Condition * Laps	7	120.799	3.907	<.001
Condition * rep	1	16.561	.001	.979
Laps * rep	7	124.232	1.713	.112
Condition * Laps * rep	7	124.232	1.138	.344

a. Dependent Variable: Power (W).

Estimated Marginal Means

1. Condition[a]

Condition	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1	71.924	5.982	18.861	59.396	84.451
2	69.579	5.427	19.122	58.225	80.932

a. Dependent Variable: Power (W).

2. Laps[a]

Laps	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1	65.870	4.131	20.721	57.271	74.469
2	69.345	4.134	20.721	60.741	77.949
3	70.173	4.136	20.721	61.565	78.780
4	70.220	4.136	20.721	61.611	78.829
5	70.850	4.136	20.721	62.241	79.460
6	70.870	4.136	20.721	62.262	79.477
7	72.461	4.134	20.721	63.857	81.066
8	76.220	4.131	20.721	67.621	84.819

a. Dependent Variable: Power (W).

3. rep[a]

rep	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1.00	69.882	4.346	24.517	60.921	78.842
2.00	71.621	4.020	18.692	63.196	80.045

a. Dependent Variable: Power (W).

4. Condition * Laps[a]

Condition	Laps	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1	71.111	6.116	20.550	58.375	83.847
	2	71.167	6.120	20.550	58.422	83.911
	3	70.278	6.123	20.550	57.528	83.027
	4	69.667	6.124	20.550	56.914	82.419
	5	70.667	6.124	20.550	57.914	83.419
	6	70.611	6.123	20.550	57.862	83.361
	7	73.056	6.120	20.550	60.311	85.800
	8	78.833	6.116	20.550	66.097	91.570
2	1	60.629	5.556	20.931	49.072	72.185
	2	67.523	5.559	20.931	55.960	79.086
	3	70.067	5.561	20.931	58.500	81.635
	4	70.773	5.562	20.931	59.203	82.343
	5	71.034	5.562	20.931	59.464	82.604
	6	71.129	5.561	20.931	59.561	82.696
	7	71.867	5.559	20.931	60.304	83.431
	8	73.606	5.556	20.931	62.050	85.163

a. Dependent Variable: Power (W).

5. Condition * rep[a]

Condition	rep	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1.00	71.083	6.411	24.111	57.854	84.313
	2.00	72.764	5.966	18.692	60.263	85.265
2	1.00	68.680	5.870	25.003	56.590	80.769
	2.00	70.477	5.391	18.692	59.181	81.774

a. Dependent Variable: Power (W).

6. Laps * rep[a]

Laps	rep	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1.00	62.437	4.579	29.515	53.079	71.794
	2.00	69.303	4.105	20.294	60.748	77.858
2	1.00	66.644	4.581	29.515	57.282	76.007
	2.00	72.045	4.108	20.294	63.485	80.606
3	1.00	67.679	4.583	29.515	58.313	77.044
	2.00	72.667	4.109	20.294	64.103	81.230
4	1.00	69.303	4.583	29.515	59.936	78.670
	2.00	71.136	4.110	20.294	62.571	79.702
5	1.00	70.958	4.583	29.515	61.591	80.325
	2.00	70.742	4.110	20.294	62.177	79.308
6	1.00	71.527	4.583	29.515	62.162	80.893
	2.00	70.212	4.109	20.294	61.649	78.776
7	1.00	72.913	4.581	29.515	63.551	82.275
	2.00	72.010	4.108	20.294	63.450	80.570
8	1.00	77.591	4.579	29.515	68.233	86.948
	2.00	74.848	4.105	20.294	66.293	83.404

a. Dependent Variable: Power (W).

7. Condition * Laps * rep[a]

Condition	Laps	rep	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1	1.00	68.889	6.743	28.885	55.095	82.683
		2.00	73.333	6.091	20.295	60.639	86.027
	2	1.00	68.333	6.747	28.885	54.532	82.134
		2.00	74.000	6.095	20.295	61.298	86.702
	3	1.00	67.222	6.749	28.885	53.416	81.028
		2.00	73.333	6.097	20.295	60.626	86.041
	4	1.00	68.333	6.750	28.885	54.525	82.142
		2.00	71.000	6.099	20.295	58.290	83.710
	5	1.00	70.667	6.750	28.885	56.858	84.475
		2.00	70.667	6.099	20.295	57.957	83.377
	6	1.00	70.889	6.749	28.885	57.083	84.695
		2.00	70.333	6.097	20.295	57.626	83.041
	7	1.00	73.000	6.747	28.885	59.199	86.801
		2.00	73.111	6.095	20.295	60.409	85.813
	8	1.00	81.333	6.743	28.885	67.539	95.127
		2.00	76.333	6.091	20.295	63.639	89.027
2	1	1.00	55.984	6.196	30.272	43.336	68.633
		2.00	65.273	5.505	20.294	53.800	76.745
	2	1.00	64.955	6.199	30.272	52.300	77.610
		2.00	70.091	5.508	20.294	58.612	81.570
	3	1.00	68.135	6.201	30.272	55.476	80.794
		2.00	72.000	5.510	20.294	60.517	83.483
	4	1.00	70.273	6.202	30.272	57.612	82.935
		2.00	71.273	5.511	20.294	59.787	82.758
	5	1.00	71.250	6.202	30.272	58.588	83.911
		2.00	70.818	5.511	20.294	59.333	82.304
	6	1.00	72.166	6.201	30.272	59.507	84.825
		2.00	70.091	5.510	20.294	58.608	81.574
	7	1.00	72.826	6.199	30.272	60.170	85.481
		2.00	70.909	5.508	20.294	59.430	82.388
	8	1.00	73.849	6.196	30.272	61.200	86.497
		2.00	73.364	5.505	20.294	61.891	84.836

a. Dependent Variable: Power (W).

Mixed Model Analyses

RPE

Mixed Model Analysis

Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Condition	2		1		
	Laps	8		7		
	Condition * Laps	16		7		
	cond_order	2		1		
	Condition * cond_order	4		1		
Random Effects	Participant#	20	Variance Components	1		
Repeated Measures 1 Repeated Measures 2	Condition Laps	16	Kronecker product of UN and AR1	4	Participant#	20
Total		69		23		

a. Dependent Variable: RPE_mean.

Information Criteria[a]

-2 Restricted Log Likelihood	559.74972592
Akaike's Information Criterion (AIC)	569.74972592
Hurvich and Tsai's Criterion (AICC)	569.95242863
Bozdogan's Criterion (CAIC)	593.30186101
Schwarz's Bayesian Criterion (BIC)	588.30186101

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: RPE_mean.

Fixed Effects

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	18.507	220.554	<.001
Condition	1	16.800	4.141	.058
Laps	7	120.525	31.434	<.001
Condition * Laps	7	144.710	.366	.921
cond_order	1	16.200	8.110	.012
Condition * cond_order	1	17.999	.552	.467

a. Dependent Variable: RPE_mean.

Covariance Parameters

Estimates of Covariance Parameters[a,b]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Repeated Measures 1: Condition	UN (1,1)	.991	.257	3.859	<.001	.596	1.646
	UN (2,1)	.273	.102	2.664	.008	.072	.474
	UN (2,2)	1.007	.253	3.978	<.001	.615	1.649
Repeated Measures 2: Laps	AR1 rho	.864	.035	24.798	<.001	.778	.918
Participant#	Variance	1.579	.681	2.320	.020	.678	3.676

a. Dependent Variable: RPE_mean.

b. The estimate of AR1 for Laps is fixed to 1 during the model building

Estimated Marginal Means

1. Condition[a]

Condition	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1	4.641	.347	22.737	3.924	5.359
2	5.101	.347	22.937	4.383	5.819

a. Dependent Variable: RPE_mean.

2. Laps[a]

Laps	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	3.276	.342	21.992	2.566	3.986
2	3.988	.343	21.992	3.278	4.699
3	4.438	.343	21.992	3.727	5.149
4	4.763	.343	21.992	4.052	5.475
5	5.201	.343	21.992	4.489	5.912
6	5.413	.343	21.992	4.702	6.124
7	5.663	.343	21.992	4.953	6.374
8	6.226	.342	21.992	5.516	6.936

a. Dependent Variable: RPE_mean.

3. Condition * Laps[a]

Condition	Laps	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1	3.082	.368	28.481	2.329	3.834
	2	3.857	.368	28.481	3.104	4.610
	3	4.282	.368	28.481	3.528	5.036
	4	4.557	.368	28.481	3.803	5.311
	5	4.932	.368	28.481	4.178	5.686
	6	5.107	.368	28.481	4.353	5.861
	7	5.382	.368	28.481	4.629	6.135
	8	5.932	.368	28.481	5.179	6.684
2	1	3.470	.369	28.801	2.716	4.224
	2	4.120	.369	28.801	3.365	4.874
	3	4.595	.369	28.801	3.839	5.350
	4	4.970	.369	28.801	4.214	5.725
	5	5.470	.369	28.801	4.714	6.225
	6	5.720	.369	28.801	4.964	6.475
	7	5.945	.369	28.801	5.190	6.699
	8	6.520	.369	28.801	5.766	7.274

a. Dependent Variable: RPE_mean.

4. cond_order[a]

cond_order	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1.00	5.182	.346	22.703	4.466	5.898
2.00	4.560	.346	22.722	3.844	5.276

a. Dependent Variable: RPE_mean.

5. Condition * cond_order[a]

Condition	cond_order	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1.00	4.710	.512	22.320	3.650	5.771
	2.00	4.572	.462	22.397	3.614	5.530
2	1.00	5.654	.463	22.590	4.695	6.613
	2.00	4.548	.513	22.511	3.487	5.610

a. Dependent Variable: RPE_mean.

Completion Time

Mixed Model Analysis

Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Condition	2		1		
	Laps	8		7		
	Condition * Laps	16		7		
	cond_order	2		1		
	Condition * cond_order	4		1		
Random Effects	Participant#	20	Variance Components	1		
Repeated Measures 1 Repeated Measures 2	Condition Laps	16	Kronecker product of UN and AR1	4	Participant#	20
Total		69		23		

a. Dependent Variable: Times_mean.

Information Criteria[a]

-2 Restricted Log Likelihood	2474.85974294
Akaike's Information Criterion (AIC)	2484.85974294
Hurvich and Tsai's Criterion (AICC)	2485.06244564
Bozdogan's Criterion (CAIC)	2508.41187803
Schwarz's Bayesian Criterion (BIC)	2503.41187803

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Times_mean.

Fixed Effects

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	18.459	720.042	<.001
Condition	1	24.416	1.321	.261
Laps	7	125.102	5.648	<.001
Condition * Laps	7	130.062	.851	.547
cond_order	1	24.873	3.999	.057
Condition * cond_order	1	18.306	.812	.379

a. Dependent Variable: Times_mean.

Covariance Parameters

Estimates of Covariance Parameters[a,b]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Repeated Measures 1: Condition	UN (1,1)	457.516	93.669	4.884	<.001	306.292	683.402
	UN (2,1)	1.140	25.918	.044	.965	-49.658	51.939
	UN (2,2)	192.083	38.944	4.932	<.001	129.095	285.803
Repeated Measures 2: Laps	AR1 rho	.737	.051	14.506	<.001	.620	.822
Participant#	Variance	1298.153	455.609	2.849	.004	652.502	2582.674

a. Dependent Variable: Times_mean.

b. The estimate of AR1 for Laps is fixed to 1 during the model building

Estimated Marginal Means

1. Condition[a]

Condition	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1	227.633	8.841	22.434	209.319	245.947
2	222.916	8.439	18.903	205.247	240.586

a. Dependent Variable: Times_mean.

2. Laps[a]

Laps	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1	234.133	8.626	20.540	216.170	252.095
2	227.208	8.631	20.540	209.234	245.181
3	227.320	8.635	20.540	209.339	245.301

4	226.195	8.636	20.540	208.211	244.180
5	224.083	8.636	20.540	206.098	242.067
6	226.308	8.635	20.540	208.327	244.289
7	222.383	8.631	20.540	204.409	240.356
8	214.570	8.626	20.540	196.608	232.533

a. Dependent Variable: Times_mean.

3. Condition * Laps[a]

Condition	Laps	Mean	Std. Error	df	95% Confidence Interval Lower Bound	Upper Bound
1	1	235.574	9.452	28.738	216.235	254.912
	2	228.374	9.457	28.738	209.025	247.723
	3	232.124	9.460	28.738	212.768	251.479
	4	230.274	9.462	28.738	210.915	249.633
	5	226.724	9.462	28.738	207.365	246.083
	6	230.224	9.460	28.738	210.868	249.579
	7	223.374	9.457	28.738	204.025	242.723
	8	214.399	9.452	28.738	195.060	233.737
2	1	232.691	8.709	21.436	214.602	250.781
	2	226.041	8.714	21.436	207.942	244.141
	3	222.516	8.718	21.436	204.410	240.623
	4	222.116	8.719	21.436	204.006	240.227
	5	221.441	8.719	21.436	203.331	239.552
	6	222.391	8.718	21.436	204.285	240.498
	7	221.391	8.714	21.436	203.292	239.491
	8	214.741	8.709	21.436	196.652	232.831

a. Dependent Variable: Times_mean.

4. cond_order[a]

cond_order	Mean	Std. Error	df	95% Confidence Interval Lower Bound	Upper Bound
1.00	221.311	8.645	20.715	203.318	239.305
2.00	229.238	8.607	20.384	211.306	247.171

a. Dependent Variable: Times_mean.

5. Condition * cond_order[a]

Condition	cond_order	Mean	Std. Error	df	95% Confidence Interval	
					Lower Bound	Upper Bound
1	1.00	216.121	13.078	22.210	189.014	243.228
	2.00	239.146	11.830	22.251	214.628	263.663
2	1.00	226.502	11.306	18.821	202.823	250.180
	2.00	219.331	12.502	18.803	193.146	245.517

a. Dependent Variable: Times_mean.

Success Rate

Mixed Model Analysis

Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Condition	2		1		
	Laps	8		7		
	Condition * Laps	16		7		
	cond_order	2		1		
	Condition * cond_order	4		1		
Random Effects	Participant#	20	Variance Components	1		
Repeated Measures 1 Repeated Measures 2	Condition Laps	16	Kronecker product of UN and AR1	4	Participant#	20
Total		69		23		

a. Dependent Variable: SuccessRate_mean.

Information Criteria[a]

-2 Restricted Log Likelihood	-975.48126149
Akaike's Information Criterion (AIC)	-965.48126149
Hurvich and Tsai's Criterion (AICC)	-965.27292815
Bozdogan's Criterion (CAIC)	-942.06336265
Schwarz's Bayesian Criterion (BIC)	-947.06336265

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: SuccessRate_mean.

Fixed Effects

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	17.358	6722.938	<.001
Condition	1	65.005	1.106	.297
Laps	7	117.745	.358	.925
Condition * Laps	7	124.136	.584	.768
cond_order	1	67.215	.094	.760
Condition * cond_order	1	17.331	1.105	.308

a. Dependent Variable: SuccessRate_mean.

Covariance Parameters

Estimates of Covariance Parameters[a,b]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Repeated Measures 1: Condition	UN (1,1)	.001	.000	7.202	<.001	.001	.002
	UN (2,1)	9.181E-5	.000	.637	.524	.000	.000
	UN (2,2)	.002	.000	7.853	<.001	.001	.002
Repeated Measures 2: Laps	AR1 rho	.159	.071	2.242	.025	.018	.294
Participant#	Variance	.001	.000	2.430	.015	.000	.002

a. Dependent Variable: SuccessRate_mean.

b. The estimate of AR1 for Laps is fixed to 1 during the model building

Estimated Marginal Means

1. Condition[a]

Condition	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1	.543	.007	21.533	.528	.557
2	.548	.007	24.015	.533	.563

a. Dependent Variable: SuccessRate_mean.

2. Laps[a]

Laps	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	.550	.009	53.844	.532	.568
2	.546	.009	53.844	.528	.564
3	.548	.009	53.844	.530	.566
4	.551	.009	53.844	.533	.569
5	.546	.009	53.844	.528	.564
6	.540	.009	53.844	.521	.558
7	.541	.009	53.844	.523	.559
8	.541	.009	53.844	.523	.559

a. Dependent Variable: SuccessRate_mean.

3. Condition * Laps[a]

Condition	Laps	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1	.545	.011	78.555	.524	.566
	2	.541	.011	78.555	.520	.562
	3	.536	.011	78.555	.515	.558
	4	.544	.011	78.555	.523	.565
	5	.548	.011	78.555	.527	.569
	6	.541	.011	78.555	.520	.563
	7	.545	.011	78.555	.524	.566
	8	.539	.011	78.555	.518	.560
2	1	.554	.011	98.635	.532	.577
	2	.551	.011	98.635	.529	.574
	3	.559	.011	98.635	.536	.581
	4	.557	.011	98.635	.535	.580
	5	.544	.011	98.635	.522	.567
	6	.538	.011	98.635	.515	.560
	7	.537	.011	98.635	.515	.560
	8	.543	.011	98.635	.521	.566

a. Dependent Variable: SuccessRate_mean.

4. cond_order[a]

cond_order	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1.00	.545	.007	22.398	.530	.559
2.00	.546	.007	23.407	.531	.561

a. Dependent Variable: SuccessRate_mean.

5. Condition * cond_order[a]

Condition	cond_order	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1.00	.535	.010	20.847	.513	.556
	2.00	.550	.010	22.328	.531	.570
2	1.00	.554	.010	23.992	.534	.574
	2.00	.542	.011	23.987	.520	.564

a. Dependent Variable: SuccessRate_mean.

Heart Rate

Mixed Model Analysis

Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Condition	2		1		
	Laps	8		7		
	Condition * Laps	16		7		
	cond_order	2		1		
	Condition * cond_order	4		1		
Random Effects	Participant#	20	Variance Components	1		
Repeated Measures 1 Repeated Measures 2	Condition Laps	16	Kronecker product of UN and AR1	4	Participant#	20
Total		69		23		

a. Dependent Variable: HRbpm_mean.

Information Criteria[a]

-2 Restricted Log Likelihood	1788.82984701
Akaike's Information Criterion (AIC)	1798.82984701
Hurvich and Tsai's Criterion (AICC)	1799.03254971
Bozdogan's Criterion (CAIC)	1822.38198210
Schwarz's Bayesian Criterion (BIC)	1817.38198210

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: HRbpm_mean.

Fixed Effects

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	18.515	960.329	<.001
Condition	1	18.964	3.678	.070
Laps	7	130.752	51.720	<.001
Condition * Laps	7	138.802	1.194	.310
cond_order	1	18.026	.001	.972
Condition * cond_order	1	18.145	.562	.463

a. Dependent Variable: HRbpm_mean.

Covariance Parameters

Estimates of Covariance Parameters[a,b]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Repeated Measures 1: Condition	UN (1,1)	127.546	36.699	3.475	<.001	72.568	224.175
	UN (2,1)	67.986	21.946	3.098	.002	24.972	111.000
	UN (2,2)	99.243	29.387	3.377	<.001	55.545	177.317
Repeated Measures 2: Laps	AR1 rho	.923	.022	42.291	<.001	.866	.956
Participant#	Variance	276.347	118.872	2.325	.020	118.934	642.101

a. Dependent Variable: HRbpm_mean.

b. The estimate of AR1 for Laps is fixed to 1 during the model building

Estimated Marginal Means

1. Condition[a]

Condition	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1	132.326	4.501	21.714	122.985	141.667
2	136.032	4.371	19.253	126.892	145.172

a. Dependent Variable: HRbpm_mean.

2. Laps[a]

Laps	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	114.985	4.428	20.268	105.756	124.215
2	129.435	4.430	20.268	120.201	138.669
3	134.148	4.432	20.268	124.911	143.385
4	136.060	4.433	20.268	126.821	145.299
5	137.448	4.433	20.268	128.209	146.686
6	138.485	4.432	20.268	129.248	147.722
7	139.823	4.430	20.268	130.589	149.057
8	143.048	4.428	20.268	133.818	152.277

a. Dependent Variable: HRbpm_mean.

3. Condition * Laps[a]

Condition	Laps	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1	114.351	4.634	24.323	104.793	123.909
	2	128.826	4.636	24.323	119.264	138.388
	3	132.626	4.638	24.323	123.061	142.191
	4	134.026	4.639	24.323	124.459	143.593
	5	134.926	4.639	24.323	125.359	144.493
	6	135.751	4.638	24.323	126.186	145.316
	7	137.301	4.636	24.323	127.739	146.863
	8	140.801	4.634	24.323	131.243	150.359
2	1	115.619	4.478	21.198	106.313	124.926
	2	130.044	4.480	21.198	120.733	139.356
	3	135.669	4.481	21.198	126.355	144.984
	4	138.094	4.482	21.198	128.778	147.410
	5	139.969	4.482	21.198	130.653	149.285
	6	141.219	4.481	21.198	131.905	150.534
	7	142.344	4.480	21.198	133.033	151.656
	8	145.294	4.478	21.198	135.988	154.601

a. Dependent Variable: HRbpm_mean.

4. cond_order[a]

cond_order	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1.00	134.212	4.437	20.568	124.973	143.452
2.00	134.145	4.425	20.333	124.925	143.366

a. Dependent Variable: HRbpm_mean.

5. Condition * cond_order[a]

Condition	cond_order	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1.00	135.587	6.659	21.424	121.756	149.418
	2.00	129.065	6.011	21.478	116.581	141.550
2	1.00	132.838	5.840	19.072	120.617	145.059
	2.00	139.226	6.471	19.031	125.684	152.768

a. Dependent Variable: HRbpm_mean.

Speed

Mixed Model Analysis

Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Condition	2		1		
	Laps	8		7		
	Condition * Laps	16		7		
	cond_order	2		1		
	Condition * cond_order	4		1		
Random Effects	Participant#	20	Variance Components	1		
Repeated Measures 1 Repeated Measures 2	Condition Laps	16	Kronecker product of UN and AR1	4	Participant#	20
Total		69		23		

a. Dependent Variable: Speedmph_mean.

Information Criteria[a]

-2 Restricted Log Likelihood	163.00866266
Akaike's Information Criterion (AIC)	173.00866266
Hurvich and Tsai's Criterion (AICC)	173.21136536
Bozdogan's Criterion (CAIC)	196.56079774
Schwarz's Bayesian Criterion (BIC)	191.56079774

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Speedmph_mean.

Fixed Effects

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	18.121	824.723	<.001
Condition	1	19.476	1.712	.206
Laps	7	131.375	11.383	<.001
Condition * Laps	7	132.706	2.263	.033
cond_order	1	18.500	1.806	.195
Condition * cond_order	1	17.913	.841	.371

a. Dependent Variable: Speedmph_mean.

Covariance Parameters

Estimates of Covariance Parameters[a,b]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Repeated Measures 1: Condition	UN (1,1)	.471	.142	3.311	<.001	.260	.850
	UN (2,1)	.160	.069	2.337	.019	.026	.295
	UN (2,2)	.493	.149	3.314	<.001	.273	.891
Repeated Measures 2: Laps	AR1 rho	.933	.020	47.769	<.001	.882	.962
Participant#	Variance	1.727	.671	2.571	.010	.806	3.700

a. Dependent Variable: Speedmph_mean.

b. The estimate of AR1 for Laps is fixed to 1 during the model building

Estimated Marginal Means

1. Condition[a]

Condition	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1	9.181	.333	20.235	8.487	9.875
2	9.397	.335	20.860	8.701	10.093

a. Dependent Variable: Speedmph_mean.

2. Laps[a]

Laps	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	8.913	.328	19.052	8.228	9.599
2	9.211	.328	19.052	8.525	9.897
3	9.295	.328	19.052	8.609	9.980
4	9.270	.328	19.052	8.584	9.956
5	9.288	.328	19.052	8.602	9.974
6	9.301	.328	19.052	8.615	9.987
7	9.386	.328	19.052	8.700	10.072
8	9.648	.328	19.052	8.963	10.334

a. Dependent Variable: Speedmph_mean.

3. Condition * Laps

Estimates[a]

Condition	Laps	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1	8.905	.339	21.619	8.202	9.609
	2	9.150	.339	21.619	8.447	9.854
	3	9.140	.339	21.619	8.437	9.844
	4	9.085	.339	21.619	8.381	9.789
	5	9.113	.339	21.619	8.409	9.817
	6	9.153	.339	21.619	8.449	9.857
	7	9.303	.339	21.619	8.599	10.007
	8	9.598	.339	21.619	8.894	10.301
2	1	8.921	.341	22.396	8.215	9.627
	2	9.271	.341	22.396	8.565	9.977
	3	9.449	.341	22.396	8.742	10.155
	4	9.454	.341	22.396	8.747	10.160
	5	9.464	.341	22.396	8.757	10.170
	6	9.449	.341	22.396	8.742	10.155
	7	9.469	.341	22.396	8.762	10.175
	8	9.699	.341	22.396	8.993	10.405

a. Dependent Variable: Speedmph_mean.

Pairwise Comparisons[a]

Laps	(I) Condition	(J) Condition	Mean Difference (I-J)	Std. Error	df	Sig.[b]	95% Confidence Interval for Difference[b] Lower Bound	Upper Bound
1	1	2	-.016	.180	26.479	.931	-.385	.354
	2	1	.016	.180	26.479	.931	-.354	.385
2	1	2	-.121	.180	26.479	.508	-.490	.249
	2	1	.121	.180	26.479	.508	-.249	.490
3	1	2	-.308	.180	26.479	.098	-.678	.061
	2	1	.308	.180	26.479	.098	-.061	.678
4	1	2	-.368	.180	26.479	.051	-.738	.001
	2	1	.368	.180	26.479	.051	-.001	.738
5	1	2	-.351	.180	26.479	.062	-.720	.019
	2	1	.351	.180	26.479	.062	-.019	.720
6	1	2	-.296	.180	26.479	.112	-.665	.074
	2	1	.296	.180	26.479	.112	-.074	.665
7	1	2	-.166	.180	26.479	.365	-.535	.204
	2	1	.166	.180	26.479	.365	-.204	.535
8	1	2	-.101	.180	26.479	.580	-.470	.269
	2	1	.101	.180	26.479	.580	-.269	.470

Based on estimated marginal means

a. Dependent Variable: Speedmph_mean.

b. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

Univariate Tests[a]

Laps	Numerator df	Denominator df	F	Sig.
1	1	26.479	.008	.931
2	1	26.479	.451	.508
3	1	26.479	2.935	.098
4	1	26.479	4.189	.051
5	1	26.479	3.800	.062
6	1	26.479	2.702	.112
7	1	26.479	.849	.365
8	1	26.479	.314	.580

Each F tests the simple effects of Condition within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

a. Dependent Variable: Speedmph_mean.

4. cond_order[a]

cond_order	Mean	Std. Error	df	95% Confidence Interval Lower Bound	Upper Bound
1.00	9.397	.333	20.458	8.703	10.091
2.00	9.181	.333	20.518	8.486	9.875

a. Dependent Variable: Speedmph_mean.

5. Condition * cond_order[a]

Condition	cond_order	Mean	Std. Error	df	95% Confidence Interval Lower Bound	Upper Bound
1	1.00	9.585	.493	20.070	8.557	10.613
	2.00	8.777	.445	20.101	7.848	9.706
2	1.00	9.210	.448	20.711	8.278	10.141
	2.00	9.584	.496	20.678	8.553	10.616

a. Dependent Variable: Speedmph_mean.

Cadence

Mixed Model Analysis

Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Condition	2		1		
	Laps	8		7		
	Condition * Laps	16		7		
	cond_order	2		1		
	Condition * cond_order	4		1		
Random Effects	Participant#	20	Variance Components	1		
Repeated Measures 1 Repeated Measures 2	Condition Laps	16	Kronecker product of UN and AR1	4	Participant#	20
Total		69		23		

a. Dependent Variable: Cadencerpm_mean.

Information Criteria[a]

-2 Restricted Log Likelihood	1459.13885049
Akaike's Information Criterion (AIC)	1469.13885049
Hurvich and Tsai's Criterion (AICC)	1469.34155319
Bozdogan's Criterion (CAIC)	1492.69098558
Schwarz's Bayesian Criterion (BIC)	1487.69098558

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Cadencerpm_mean.

Fixed Effects

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	18.274	835.006	<.001
Condition	1	19.961	1.528	.231
Laps	7	130.831	8.463	<.001
Condition * Laps	7	133.188	2.622	.014
cond_order	1	18.966	1.483	.238
Condition * cond_order	1	18.068	.961	.340

a. Dependent Variable: Cadencerpm_mean.

Covariance Parameters

Estimates of Covariance Parameters[a,b]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Repeated Measures 1: Condition	UN (1,1)	30.925	9.335	3.313	<.001	17.114	55.881
	UN (2,1)	12.048	5.066	2.378	.017	2.119	21.977
	UN (2,2)	40.846	12.059	3.387	<.001	22.901	72.855
Repeated Measures 2: Laps	AR1 rho	.934	.019	48.934	<.001	.884	.963
Participant#	Variance	130.707	50.493	2.589	.010	61.302	278.691

a. Dependent Variable: Cadencerpm_mean.

b. The estimate of AR1 for Laps is fixed to 1 during the model building

Estimated Marginal Means

1. Condition[a]

Condition	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1	80.287	2.860	19.578	74.313	86.262
2	82.046	2.934	21.760	75.957	88.135

a. Dependent Variable: Cadencerpm_mean.

2. Laps[a]

Laps	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	78.537	2.844	19.193	72.588	84.486
2	80.349	2.845	19.193	74.399	86.300
3	81.137	2.845	19.193	75.185	87.088
4	80.949	2.846	19.193	74.997	86.901
5	81.012	2.846	19.193	75.060	86.964
6	81.237	2.845	19.193	75.285	87.188
7	81.949	2.845	19.193	75.999	87.900
8	84.162	2.844	19.193	78.213	90.111

a. Dependent Variable: Cadencerpm_mean.

3. Condition * Laps

Estimates[a]

Condition	Laps	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1	78.459	2.905	20.770	72.414	84.505
	2	79.884	2.906	20.770	73.837	85.931
	3	79.784	2.906	20.770	73.736	85.832
	4	79.359	2.907	20.770	73.311	85.408
	5	79.509	2.907	20.770	73.461	85.558
	6	80.034	2.906	20.770	73.986	86.082
	7	81.384	2.906	20.770	75.337	87.431
	8	83.884	2.905	20.770	77.839	89.930
2	1	78.615	2.992	23.449	72.432	84.798
	2	80.815	2.993	23.449	74.630	86.999
	3	82.490	2.993	23.449	76.304	88.675
	4	82.540	2.994	23.449	76.354	88.726
	5	82.515	2.994	23.449	76.329	88.701
	6	82.440	2.993	23.449	76.254	88.625
	7	82.515	2.993	23.449	76.330	88.699
	8	84.440	2.992	23.449	78.257	90.623

a. Dependent Variable: Cadencerpm_mean.

Pairwise Comparisons[a]

Laps	(I) Condition	(J) Condition	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c] Lower Bound	Upper Bound
1	1	2	-.156	1.550	27.025	.921	-3.336	3.025
	2	1	.156	1.550	27.025	.921	-3.025	3.336
2	1	2	-.931	1.550	27.025	.553	-4.111	2.250
	2	1	.931	1.550	27.025	.553	-2.250	4.111
3	1	2	-2.706	1.550	27.025	.092	-5.886	.475
	2	1	2.706	1.550	27.025	.092	-.475	5.886
4	1	2	-3.181*	1.550	27.025	.050	-6.361	-4.558E-6
	2	1	3.181*	1.550	27.025	.050	4.558E-6	6.361
5	1	2	-3.006	1.550	27.025	.063	-6.186	.175
	2	1	3.006	1.550	27.025	.063	-.175	6.186
6	1	2	-2.406	1.550	27.025	.132	-5.586	.775
	2	1	2.406	1.550	27.025	.132	-.775	5.586
7	1	2	-1.131	1.550	27.025	.472	-4.311	2.050
	2	1	1.131	1.550	27.025	.472	-2.050	4.311
8	1	2	-.556	1.550	27.025	.723	-3.736	2.625
	2	1	.556	1.550	27.025	.723	-2.625	3.736

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Cadencerpm_mean.

c. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

Univariate Tests[a]

Laps	Numerator df	Denominator df	F	Sig.
1	1	27.025	.010	.921
2	1	27.025	.360	.553
3	1	27.025	3.046	.092
4	1	27.025	4.210	.050
5	1	27.025	3.759	.063
6	1	27.025	2.408	.132
7	1	27.025	.532	.472
8	1	27.025	.128	.723

Each F tests the simple effects of Condition within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

a. Dependent Variable: Cadencerpm_mean.

4. cond_order[a]

cond_order	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1.00	82.013	2.890	20.506	75.994	88.032
2.00	80.320	2.897	20.715	74.290	86.350

a. Dependent Variable: Cadencerpm_mean.

5. Condition * cond_order[a]

Condition	cond_order	Mean	Std. Error	df	95% Confidence Interval	
					Lower Bound	Upper Bound
1	1.00	83.878	4.237	19.434	75.024	92.732
	2.00	76.696	3.827	19.461	68.698	84.694
2	1.00	80.149	3.925	21.597	72.000	88.297
	2.00	83.943	4.344	21.560	74.923	92.964

a. Dependent Variable: Cadencerpm_mean.

Power

Mixed Model Analysis

Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Condition	2		1		
	Laps	8		7		
	Condition * Laps	16		7		
	cond_order	2		1		
	Condition * cond_order	4		1		
Random Effects	Participant#	20	Variance Components	1		
Repeated Measures 1 Repeated Measures 2	Condition Laps	16	Kronecker product of UN and AR1	4	Participant#	20
Total		69		23		

a. Dependent Variable: PowerW_mean.

Information Criteria[a]

-2 Restricted Log Likelihood	1744.31546393
Akaike's Information Criterion (AIC)	1754.31546393
Hurvich and Tsai's Criterion (AICC)	1754.51816663
Bozdogan's Criterion (CAIC)	1777.86759901
Schwarz's Bayesian Criterion (BIC)	1772.86759901

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: PowerW_mean.

Fixed Effects

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	18.109	330.405	<.001
Condition	1	20.924	2.492	.129
Laps	7	128.257	9.237	<.001
Condition * Laps	7	134.843	2.620	.014
cond_order	1	20.147	1.172	.292
Condition * cond_order	1	17.951	.725	.406

a. Dependent Variable: PowerW_mean.

Covariance Parameters

Estimates of Covariance Parameters[a,b]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Repeated Measures 1: Condition	UN (1,1)	41.933	10.760	3.897	<.001	25.359	69.337
	UN (2,1)	10.306	4.990	2.065	.039	.524	20.087
	UN (2,2)	50.990	12.759	3.997	<.001	31.225	83.267
Repeated Measures 2: Laps	AR1 rho	.863	.033	25.912	<.001	.782	.916
Participant#	Variance	268.829	96.255	2.793	.005	133.260	542.313

a. Dependent Variable: PowerW_mean.

b. The estimate of AR1 for Laps is fixed to 1 during the model building

Estimated Marginal Means

1. Condition[a]

Condition	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1	68.676	3.909	19.223	60.501	76.851
2	71.199	3.951	20.169	62.963	79.436

a. Dependent Variable: PowerW_mean.

2. Laps[a]

Laps	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	66.139	3.903	19.162	57.976	74.303
2	68.864	3.904	19.162	60.697	77.031
3	70.152	3.905	19.162	61.983	78.321
4	69.464	3.906	19.162	61.294	77.635
5	69.827	3.906	19.162	61.657	77.997
6	69.852	3.905	19.162	61.683	78.021
7	70.839	3.904	19.162	62.672	79.006
8	74.364	3.903	19.162	66.201	82.528

a. Dependent Variable: PowerW_mean.

3. Condition * Laps

Estimates[a]

Condition	Laps	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1	66.836	3.989	20.777	58.534	75.137
	2	67.986	3.991	20.777	59.681	76.290
	3	68.636	3.992	20.777	60.329	76.943
	4	67.061	3.992	20.777	58.753	75.369
	5	67.561	3.992	20.777	59.253	75.869
	6	67.986	3.992	20.777	59.679	76.293
	7	69.561	3.991	20.777	61.256	77.865
	8	73.786	3.989	20.777	65.484	82.087
2	1	65.443	4.048	22.181	57.053	73.833
	2	69.743	4.049	22.181	61.350	78.136
	3	71.668	4.050	22.181	63.273	80.063
	4	71.868	4.051	22.181	63.472	80.265
	5	72.093	4.051	22.181	63.697	80.490
	6	71.718	4.050	22.181	63.323	80.113
	7	72.118	4.049	22.181	63.725	80.511
	8	74.943	4.048	22.181	66.553	83.333

a. Dependent Variable: PowerW_mean.

Pairwise Comparisons[a]

Laps	(I) Condition	(J) Condition	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
							Lower Bound	Upper Bound
1	1	2	1.392	1.908	36.164	.470	-2.476	5.261
	2	1	-1.392	1.908	36.164	.470	-5.261	2.476
2	1	2	-1.758	1.908	36.164	.363	-5.626	2.111
	2	1	1.758	1.908	36.164	.363	-2.111	5.626
3	1	2	-3.033	1.908	36.164	.121	-6.901	.836
	2	1	3.033	1.908	36.164	.121	-.836	6.901
4	1	2	-4.808*	1.908	36.164	.016	-8.676	-.939
	2	1	4.808*	1.908	36.164	.016	.939	8.676
5	1	2	-4.533*	1.908	36.164	.023	-8.401	-.664
	2	1	4.533*	1.908	36.164	.023	.664	8.401
6	1	2	-3.733	1.908	36.164	.058	-7.601	.136
	2	1	3.733	1.908	36.164	.058	-.136	7.601
7	1	2	-2.558	1.908	36.164	.188	-6.426	1.311
	2	1	2.558	1.908	36.164	.188	-1.311	6.426
8	1	2	-1.158	1.908	36.164	.548	-5.026	2.711
	2	1	1.158	1.908	36.164	.548	-2.711	5.026

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: PowerW_mean.

c. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

Univariate Tests[a]

Laps	Numerator df	Denominator df	F	Sig.
1	1	36.164	.533	.470
2	1	36.164	.849	.363
3	1	36.164	2.527	.121
4	1	36.164	6.350	.016
5	1	36.164	5.645	.023
6	1	36.164	3.828	.058
7	1	36.164	1.797	.188
8	1	36.164	.368	.548

Each F tests the simple effects of Condition within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

a. Dependent Variable: PowerW_mean.

4. cond_order[a]

				95% Confidence Interval	
cond_order	Mean	Std. Error	df	Lower Bound	Upper Bound
1.00	70.775	3.922	19.564	62.581	78.968
2.00	69.101	3.926	19.653	60.901	77.301

a. Dependent Variable: PowerW_mean.

5. Condition * cond_order[a]

					95% Confidence Interval	
Condition	cond_order	Mean	Std. Error	df	Lower Bound	Upper Bound
1	1.00	72.782	5.789	19.098	60.670	84.894
	2.00	64.570	5.234	19.121	53.620	75.521
2	1.00	68.767	5.289	20.040	57.737	79.798
	2.00	73.631	5.849	20.010	61.431	85.831

a. Dependent Variable: PowerW_mean.

Intrinsic Motivation

Mixed Model Analysis

Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Condition	2		1		
	Time	2		1		
	Condition * Time	4		1		
	cond_order	2		1		
	Condition * cond_order	4		1		
Random Effects	Participant#	20	Variance Components	1		
Repeated Measures 1 Repeated Measures 2	Condition Time	4	Kronecker product of UN and AR1	4	Participant#	20
Total		39		11		

a. Dependent Variable: IMI_mean.

Information Criteria[a]

-2 Restricted Log Likelihood	33.26200348
Akaike's Information Criterion (AIC)	43.26200348
Hurvich and Tsai's Criterion (AICC)	44.14435642
Bozdogan's Criterion (CAIC)	59.78232894
Schwarz's Bayesian Criterion (BIC)	54.78232894

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: IMI_mean.

Fixed Effects

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	18.593	1266.797	<.001
Condition	1	18.004	.008	.931
Time	1	22.032	9.063	.006
Condition * Time	1	19.002	.099	.756
cond_order	1	18.004	.636	.436
Condition * cond_order	1	18.593	1.046	.320

a. Dependent Variable: IMI_mean.

Covariance Parameters

Estimates of Covariance Parameters[a,b]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Repeated Measures 1: Condition	UN (1,1)	.058	.030	1.936	.053	.021	.160
	UN (2,1)	.054	.031	1.720	.085	-.007	.115
	UN (2,2)	.132	.051	2.588	.010	.062	.282
Repeated Measures 2: Time	AR1 rho	.711	.115	6.190	<.001	.409	.873
Participant#	Variance	.244	.103	2.371	.018	.107	.557

a. Dependent Variable: IMI_mean.

b. The estimate of AR1 for Time is fixed to 1 during the model building

Estimated Marginal Means

1. Condition[a]

Condition	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1	4.676	.129	17.786	4.405	4.947
2	4.671	.141	22.384	4.379	4.962

a. Dependent Variable: IMI_mean.

2. Time[a]

Time	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1	4.599	.134	19.734	4.320	4.878
2	4.748	.134	19.734	4.469	5.027

a. Dependent Variable: IMI_mean.

3. Condition * Time[a]

Condition	Time	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1	4.606	.131	18.819	4.332	4.880
	2	4.747	.131	18.819	4.473	5.020
2	1	4.592	.144	24.163	4.294	4.890
	2	4.749	.144	24.163	4.451	5.047

a. Dependent Variable: IMI_mean.

4. cond_order[a]

cond_order	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1.00	4.649	.134	20.384	4.369	4.929
2.00	4.698	.135	20.847	4.416	4.980

a. Dependent Variable: IMI_mean.

5. Condition * cond_order[a]

Condition	cond_order	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1.00	4.786	.192	17.786	4.383	5.189
	2.00	4.567	.172	17.786	4.204	4.929
2	1.00	4.512	.188	22.384	4.122	4.902
	2.00	4.830	.209	22.384	4.397	5.263

a. Dependent Variable: IMI_mean.

Mixed Model Analysis

Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Condition	2		1		
	Time	2		1		
	Condition * Time	4		1		
	cond_order	2		1		
	Condition * cond_order	4		1		
Random Effects	Participant#	20	Variance Components	1		
Repeated Measures 1 Repeated Measures 2	Condition Time	4	Kronecker product of UN and AR1	4	Participant#	20
Total		39		11		

a. Dependent Variable: Interest_mean.

Information Criteria[a]

-2 Restricted Log Likelihood	155.84039205
Akaike's Information Criterion (AIC)	165.84039205
Hurvich and Tsai's Criterion (AICC)	166.72274499
Bozdogan's Criterion (CAIC)	182.36071752
Schwarz's Bayesian Criterion (BIC)	177.36071752

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Interest_mean.

Fixed Effects

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	17.557	257.327	<.001
Condition	1	18.000	.001	.976
Time	1	21.693	8.152	.009
Condition * Time	1	19.000	3.518	.076
cond_order	1	18.000	1.289	.271
Condition * cond_order	1	17.557	.000	.991

a. Dependent Variable: Interest_mean.

Covariance Parameters

Estimates of Covariance Parameters[a,b]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Repeated Measures 1: Condition	UN (1,1)	.396	.194	2.038	.042	.151	1.036
	UN (2,1)	.357	.189	1.890	.059	-.013	.727
	UN (2,2)	.621	.243	2.555	.011	.289	1.338
Repeated Measures 2: Time	AR1 rho	.547	.163	3.361	<.001	.158	.790
Participant#	Variance	.757	.401	1.889	.059	.268	2.136

a. Dependent Variable: Interest_mean.

b. The estimate of AR1 for Time is fixed to 1 during the model building

Estimated Marginal Means

1. Condition[a]

Condition	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1	4.142	.256	17.792	3.603	4.681
2	4.138	.271	19.890	3.572	4.705

a. Dependent Variable: Interest_mean.

2. Time[a]

Time	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1	3.928	.269	20.461	3.369	4.488
2	4.351	.269	20.461	3.792	4.911

a. Dependent Variable: Interest_mean.

3. Condition * Time[a]

Condition	Time	Mean	Std. Error	df	95% Confidence Interval	
					Lower Bound	Upper Bound
1	1	3.986	.266	20.884	3.433	4.540
	2	4.297	.266	20.884	3.743	4.850
2	1	3.870	.285	23.242	3.280	4.460
	2	4.406	.285	23.242	3.816	4.996

a. Dependent Variable: Interest_mean.

4. cond_order[a]

cond_order	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1.00	4.077	.263	19.272	3.526	4.627
2.00	4.203	.265	19.478	3.650	4.756

a. Dependent Variable: Interest_mean.

5. Condition * cond_order[a]

Condition	cond_order	Mean	Std. Error	df	95% Confidence Interval	
					Lower Bound	Upper Bound
1	1.00	4.075	.382	17.792	3.273	4.878
	2.00	4.208	.342	17.792	3.488	4.927
2	1.00	4.078	.363	19.890	3.321	4.835
	2.00	4.198	.404	19.890	3.355	5.041

a. Dependent Variable: Interest_mean.

Mixed Model Analysis

Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Condition	2		1		
	Time	2		1		
	Condition * Time	4		1		
	cond_order	2		1		
	Condition * cond_order	4		1		
Random Effects	Participant#	20	Variance Components	1		
Repeated Measures 1 Repeated Measures 2	Condition Time	4	Kronecker product of UN and AR1	4	Participant#	20
Total		39		11		

a. Dependent Variable: Competence_mean.

Information Criteria[a]

-2 Restricted Log Likelihood	129.57464802
Akaike's Information Criterion (AIC)	139.57464802
Hurvich and Tsai's Criterion (AICC)	140.45700097
Bozdogan's Criterion (CAIC)	156.09497349
Schwarz's Bayesian Criterion (BIC)	151.09497349

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Competence_mean.

Fixed Effects

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	18.504	495.768	<.001
Condition	1	18.000	.638	.435
Time	1	18.859	1.497	.236
Condition * Time	1	19.000	.554	.466
cond_order	1	18.000	6.857	.017
Condition * cond_order	1	18.504	.136	.716

a. Dependent Variable: Competence_mean.

Covariance Parameters

Estimates of Covariance Parameters[a,b]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Repeated Measures 1: Condition	UN (1,1)	.118	.051	2.319	.020	.051	.274
	UN (2,1)	.048	.048	1.008	.313	-.046	.143
	UN (2,2)	.251	.087	2.869	.004	.127	.497
Repeated Measures 2: Time	AR1 rho	.409	.194	2.113	.035	-.021	.712
Participant#	Variance	.745	.275	2.710	.007	.361	1.535

a. Dependent Variable: Competence_mean.

b. The estimate of AR1 for Time is fixed to 1 during the model building

Estimated Marginal Means

1. Condition[a]

Condition	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1	4.713	.210	18.433	4.273	5.153
2	4.632	.222	22.351	4.172	5.092

a. Dependent Variable: Competence_mean.

2. Time[a]

Time	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1	4.619	.214	20.013	4.172	5.066
2	4.726	.214	20.013	4.279	5.173

a. Dependent Variable: Competence_mean.

3. Condition * Time[a]

Condition	Time	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1	4.636	.214	19.907	4.189	5.083
	2	4.790	.214	19.907	4.343	5.238
2	1	4.603	.231	25.542	4.128	5.077
	2	4.661	.231	25.542	4.187	5.135

a. Dependent Variable: Competence_mean.

4. cond_order[a]

cond_order	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1.00	4.539	.215	20.402	4.091	4.988
2.00	4.806	.217	20.798	4.355	5.256

a. Dependent Variable: Competence_mean.

5. Condition * cond_order[a]

Condition	cond_order	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1.00	4.657	.312	18.433	4.004	5.311
	2.00	4.769	.281	18.433	4.179	5.359
2	1.00	4.421	.297	22.351	3.805	5.037
	2.00	4.843	.329	22.351	4.160	5.525

a. Dependent Variable: Competence_mean.

Mixed Model Analysis

Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Condition	2		1		
	Time	2		1		
	Condition * Time	4		1		
	cond_order	2		1		
	Condition * cond_order	4		1		
Random Effects	Participant#	20	Variance Components	1		
Repeated Measures 1 Repeated Measures 2	Condition Time	4	Kronecker product of UN and AR1	4	Participant#	20
Total		39		11		

a. Dependent Variable: Effort_mean.

Information Criteria[a]

-2 Restricted Log Likelihood	135.19963966
Akaike's Information Criterion (AIC)	145.19963966
Hurvich and Tsai's Criterion (AICC)	146.08199260
Bozdogan's Criterion (CAIC)	161.71996513
Schwarz's Bayesian Criterion (BIC)	156.71996513

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Effort_mean.

Fixed Effects

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	17.562	1013.081	<.001
Condition	1	18.000	.096	.760
Time	1	19.844	.985	.333
Condition * Time	1	19.000	.493	.491
cond_order	1	18.000	.645	.432
Condition * cond_order	1	17.562	.696	.415

a. Dependent Variable: Effort_mean.

Covariance Parameters

Estimates of Covariance Parameters[a,b]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Repeated Measures 1: Condition	UN (1,1)	.447	.182	2.460	.014	.202	.992
	UN (2,1)	.223	.142	1.564	.118	-.056	.501
	UN (2,2)	.347	.165	2.109	.035	.137	.880
Repeated Measures 2: Time	AR1 rho	.602	.148	4.060	<.001	.236	.818
Participant#	Variance	.175	.198	.885	.376	.019	1.602

a. Dependent Variable: Effort_mean.

b. The estimate of AR1 for Time is fixed to 1 during the model building

Estimated Marginal Means

1. Condition[a]

Condition	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1	5.758	.195	20.761	5.351	6.164
2	5.795	.187	20.757	5.406	6.184

a. Dependent Variable: Effort_mean.

2. Time[a]

Time	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1	5.718	.191	22.511	5.322	6.113
2	5.835	.191	22.511	5.440	6.231

a. Dependent Variable: Effort_mean.

3. Condition * Time[a]

Condition	Time	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1	5.720	.208	25.637	5.293	6.147
	2	5.795	.208	25.637	5.368	6.222
2	1	5.715	.197	26.337	5.310	6.119
	2	5.875	.197	26.337	5.470	6.279

a. Dependent Variable: Effort_mean.

4. cond_order[a]

cond_order	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1.00	5.728	.191	23.065	5.332	6.124
2.00	5.824	.191	23.149	5.430	6.219

a. Dependent Variable: Effort_mean.

5. Condition * cond_order[a]

Condition	cond_order	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	1.00	5.861	.292	20.761	5.254	6.468
	2.00	5.655	.260	20.761	5.113	6.196
2	1.00	5.595	.248	20.757	5.079	6.112
	2.00	5.994	.279	20.757	5.414	6.575

a. Dependent Variable: Effort_mean.

Mixed Model Analysis

Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Condition	2		1		
	Time	2		1		
	Condition * Time	4		1		
	cond_order	2		1		
	Condition * cond_order	4		1		
Random Effects	Participant#	20	Variance Components	1		
Repeated Measures 1 Repeated Measures 2	Condition Time	4	Kronecker product of UN and AR1	4	Participant#	20
Total		39		11		

a. Dependent Variable: Pressure_mean.

Information Criteria[a]

-2 Restricted Log Likelihood	110.02476413
Akaike's Information Criterion (AIC)	120.02476413
Hurvich and Tsai's Criterion (AICC)	120.90711707
Bozdogan's Criterion (CAIC)	136.54508960
Schwarz's Bayesian Criterion (BIC)	131.54508960

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Pressure_mean.

Fixed Effects

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	18.009	130.658	<.001
Condition	1	18.000	1.142	.299
Time	1	19.087	.605	.446
Condition * Time	1	19.000	.509	.484
cond_order	1	18.000	13.984	.002
Condition * cond_order	1	18.009	.392	.539

a. Dependent Variable: Pressure_mean.

Covariance Parameters

Estimates of Covariance Parameters[a,b]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Repeated Measures 1: Condition	UN (1,1)	.091	.033	2.797	.005	.045	.183
	UN (2,1)	-.001	.023	-.049	.961	-.046	.044
	UN (2,2)	.112	.037	2.980	.003	.058	.216
Repeated Measures 2: Time	AR1 rho	.237	.220	1.080	.280	-.211	.603
Participant#	Variance	.654	.229	2.857	.004	.329	1.299

a. Dependent Variable: Pressure_mean.

b. The estimate of AR1 for Time is fixed to 1 during the model building

Estimated Marginal Means

1. Condition[a]

Condition	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1	2.110	.192	19.311	1.708	2.512
2	2.199	.194	19.880	1.794	2.603

a. Dependent Variable: Pressure_mean.

2. Time[a]

Time	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1	2.179	.191	19.001	1.779	2.579
2	2.129	.191	19.001	1.729	2.529

a. Dependent Variable: Pressure_mean.

3. Condition * Time[a]

Condition	Time	Mean	Std. Error	df	95% Confidence Interval	
					Lower Bound	Upper Bound
1	1	2.112	.197	21.115	1.703	2.522
	2	2.107	.197	21.115	1.698	2.517
2	1	2.246	.200	22.044	1.832	2.660
	2	2.151	.200	22.044	1.737	2.565

a. Dependent Variable: Pressure_mean.

4. cond_order[a]

cond_order	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1.00	2.310	.193	19.641	1.907	2.713
2.00	1.999	.193	19.698	1.596	2.402

a. Dependent Variable: Pressure_mean.

5. Condition * cond_order[a]

Condition	cond_order	Mean	Std. Error	df	95% Confidence Interval	
					Lower Bound	Upper Bound
1	1.00	2.383	.285	19.311	1.787	2.980
	2.00	1.836	.258	19.311	1.298	2.375
2	1.00	2.236	.260	19.880	1.694	2.779
	2.00	2.161	.288	19.880	1.561	2.762

a. Dependent Variable: Pressure_mean.

Mixed Model Analysis

Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Condition	2		1		
	Time	2		1		
	Condition * Time	4		1		
	cond_order	2		1		
	Condition * cond_order	4		1		
Random Effects	Participant#	20	Variance Components	1		
Repeated Measures 1 Repeated Measures 2	Condition Time	4	Kronecker product of UN and AR1	4	Participant#	20
Total		39		11		

a. Dependent Variable: Choice_mean.

Information Criteria[a]

-2 Restricted Log Likelihood	94.02757799
Akaike's Information Criterion (AIC)	104.02757799
Hurvich and Tsai's Criterion (AICC)	104.90993093
Bozdogan's Criterion (CAIC)	120.54790346
Schwarz's Bayesian Criterion (BIC)	115.54790346

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Choice_mean.

Fixed Effects

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	17.993	1173.391	<.001
Condition	1	18.001	.008	.930
Time	1	19.553	.003	.957
Condition * Time	1	19.000	.162	.692
cond_order	1	18.001	.137	.716
Condition * cond_order	1	17.993	1.165	.295

a. Dependent Variable: Choice_mean.

Covariance Parameters

Estimates of Covariance Parameters[a,b]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Repeated Measures 1: Condition	UN (1,1)	.053	.018	2.953	.003	.027	.102
	UN (2,1)	.001	.015	.089	.929	-.029	.031
	UN (2,2)	.085	.025	3.405	<.001	.048	.151
Repeated Measures 2: Time	AR1 rho	-.152	.227	-.667	.505	-.543	.294
Participant#	Variance	.605	.207	2.926	.003	.310	1.182

a. Dependent Variable: Choice_mean.

b. The estimate of AR1 for Time is fixed to 1 during the model building

Estimated Marginal Means

1. Condition[a]

Condition	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1	6.099	.179	18.469	5.723	6.475
2	6.104	.181	19.137	5.724	6.483

a. Dependent Variable: Choice_mean.

2. Time[a]

Time	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1	6.103	.181	19.137	5.724	6.482
2	6.100	.181	19.137	5.721	6.478

a. Dependent Variable: Choice_mean.

3. Condition * Time[a]

Condition	Time	Mean	Std. Error	df	95% Confidence Interval Lower Bound	Upper Bound
1	1	6.113	.184	20.263	5.730	6.496
	2	6.085	.184	20.263	5.702	6.467
2	1	6.093	.188	21.831	5.703	6.483
	2	6.115	.188	21.831	5.724	6.505

a. Dependent Variable: Choice_mean.

4. cond_order[a]

cond_order	Mean	Std. Error	df	95% Confidence Interval Lower Bound	Upper Bound
1.00	6.112	.180	18.789	5.734	6.489
2.00	6.091	.180	18.856	5.713	6.469

a. Dependent Variable: Choice_mean.

5. Condition * cond_order[a]

Condition	cond_order	Mean	Std. Error	df	95% Confidence Interval Lower Bound	Upper Bound
1	1.00	6.302	.266	18.469	5.744	6.860
	2.00	5.896	.240	18.469	5.392	6.400
2	1.00	5.922	.243	19.137	5.413	6.431
	2.00	6.286	.269	19.137	5.723	6.849

a. Dependent Variable: Choice_mean.

Mixed Model Analysis

Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Condition	2		1		
	Time	2		1		
	Condition * Time	4		1		
	cond_order	2		1		
	Condition * cond_order	4		1		
Random Effects	Participant#	20	Variance Components	1		
Repeated Measures 1 Repeated Measures 2	Condition Time	4	Kronecker product of UN and AR1	4	Participant#	20
Total		39		11		

a. Dependent Variable: Value_mean.

Information Criteria[a]

-2 Restricted Log Likelihood	133.15990805
Akaike's Information Criterion (AIC)	143.15990805
Hurvich and Tsai's Criterion (AICC)	144.04226099
Bozdogan's Criterion (CAIC)	159.68023352
Schwarz's Bayesian Criterion (BIC)	154.68023352

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Value_mean.

Fixed Effects

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	17.487	391.872	<.001
Condition	1	18.000	.690	.417
Time	1	21.315	11.122	.003
Condition * Time	1	19.000	.467	.503
cond_order	1	18.000	2.120	.163
Condition * cond_order	1	17.487	1.055	.318

a. Dependent Variable: Value_mean.

Covariance Parameters

Estimates of Covariance Parameters[a,b]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Repeated Measures 1: Condition	UN (1,1)	.134	.063	2.143	.032	.054	.336
	UN (2,1)	.074	.054	1.371	.170	-.032	.181
	UN (2,2)	.244	.087	2.793	.005	.121	.492
Repeated Measures 2: Time	AR1 rho	.445	.187	2.383	.017	.022	.732
Participant#	Variance	1.217	.445	2.736	.006	.595	2.491

a. Dependent Variable: Value_mean.

b. The estimate of AR1 for Time is fixed to 1 during the model building

Estimated Marginal Means

1. Condition[a]

Condition	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1	5.236	.263	17.924	4.683	5.789
2	5.157	.270	19.069	4.592	5.723

a. Dependent Variable: Value_mean.

2. Time[a]

Time	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1	5.047	.266	18.401	4.488	5.605
2	5.347	.266	18.401	4.788	5.905

a. Dependent Variable: Value_mean.

3. Condition * Time[a]

Condition	Time	Mean	Std. Error	df	95% Confidence Interval	
					Lower Bound	Upper Bound
1	1	5.066	.267	19.022	4.507	5.626
	2	5.406	.267	19.022	4.847	5.965
2	1	5.027	.277	20.582	4.450	5.603
	2	5.287	.277	20.582	4.711	5.864

a. Dependent Variable: Value_mean.

4. cond_order[a]

cond_order	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1.00	5.127	.266	18.525	4.569	5.686
2.00	5.266	.267	18.639	4.706	5.826

a. Dependent Variable: Value_mean.

5. Condition * cond_order[a]

Condition	cond_order	Mean	Std. Error	df	95% Confidence Interval	
					Lower Bound	Upper Bound
1	1.00	5.437	.391	17.924	4.615	6.258
	2.00	5.036	.353	17.924	4.294	5.777
2	1.00	4.818	.362	19.069	4.060	5.576
	2.00	5.496	.401	19.069	4.657	6.335

a. Dependent Variable: Value_mean.

Engagement

Mixed Model Analysis

Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Condition	2		1		
	cond_order	2		1		
	Condition * cond_order	4		1		
Random Effects	Participant#	20	Variance Components	1		
Repeated Effects	Condition	2	Diagonal	2	Participant#	20
Total		31		7		

a. Dependent Variable: Engagement_mean.

Information Criteria[a]

-2 Restricted Log Likelihood	44.50101411
Akaike's Information Criterion (AIC)	50.50101411
Hurvich and Tsai's Criterion (AICC)	51.25101411
Bozdogan's Criterion (CAIC)	58.25157093
Schwarz's Bayesian Criterion (BIC)	55.25157093

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Engagement_mean.

Fixed Effects

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	18.000	1818.579	<.001
Condition	1	18.000	.050	.826
cond_order	1	18.000	.421	.525
Condition * cond_order	1	18.000	.015	.904

a. Dependent Variable: Engagement_mean.

Covariance Parameters

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Repeated Measures	Var: [Condition=1]	.027	.038	.718	.473	.002	.417
	Var: [Condition=2]	.118	.054	2.191	.028	.048	.289
Participant#	Variance	.146	.061	2.391	.017	.064	.331

a. Dependent Variable: Engagement_mean.

Estimated Marginal Means

1. Condition[a]

Condition	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	4.310	.115	18.000	4.068	4.551
2	4.334	.117	18.000	4.090	4.579

a. Dependent Variable: Engagement_mean.

2. cond_order[a]

cond_order	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1.00	4.358	.116	24.457	4.119	4.598
2.00	4.286	.115	23.776	4.047	4.524

a. Dependent Variable: Engagement_mean.

3. Condition * cond_order[a]

Condition	cond_order	Mean	Std. Error	df	95% Confidence Interval	
					Lower Bound	Upper Bound
1	1.00	4.333	.172	18.000	3.973	4.694
	2.00	4.286	.153	18.000	3.965	4.607
2	1.00	4.383	.156	18.000	4.055	4.712
	2.00	4.286	.173	18.000	3.922	4.649

a. Dependent Variable: Engagement_mean.

VITA

Joei Velten was born in Staten Island, New York. She completed her undergraduate education at Texas Christian University, graduating Magna Cum Laude with her Bachelor of Science degree in Kinesiology. She continued her education at Florida State University, where she completed her Master of Science degree in Sport Psychology. In 2021, she began attending the University of Tennessee, Knoxville to pursue a Doctor of Philosophy degree. Her research interests are focused on human performance optimization, especially through the use of technologies such as virtual and extended realities. In 2025, she will earn her Doctor of Philosophy degree in Kinesiology with a specialization in Sport Psychology and Motor Behavior.