Learning before our Mistakes: Predicting Unintentional Injury by Predicting Error

A Dissertation

Presented in Partial Fulfillment of the Requirements for the

Degree of Doctor of Philosophy

with a

Major in Experimental Psychology

in the

College of Graduate Studies

University of Idaho

by

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May 2022

Abstract

Unintentional injury remains a significant burden on society and has attracted a broad range of research. Previous injury research has identified a host of risk factors in various injury domains such as inhibitory control, age, cognitive development, and distraction for pedestrian injury. However, much is still left to explore despite extensive work to understand injury etiology. Human error research provides a robust framework to transcend domain-specific prediction by applying performance-shaping factors. In two studies, I examined the impact of several performance-shaping factors on an injury-relevant cross-contextual behavior, multiple object tracking. Specifically, each study examines the impact of task complexity, time pressure, sensory limitations, and nonverbal working memory span on multiple object tracking. The first study examined the impact of performance-shaping factors in an abstract dot tracking task. The second study examined the impact of performance-shaping factors in a pedestrian street-crossing scenario. In both studies, increases in time pressure and sensory limitations were associated with degraded performance and a higher task failure rate. Lower nonverbal working memory spans were also associated with poorer performance and higher failure rates in both studies. In the abstract dot tracking task, an increase in task complexity led to a reduction in performance and increased failure rate, but the relationship was the opposite in the pedestrian scenario. Implications for injury prevention and etiology research are discussed along with future directions.

Acknowledgments

I have received a great deal of guidance and support throughout the process of my doctoral education.

First, I would like to express my sincerest thanks to my major professor, Dr. Benjamin Barton, whose expertise and mentorship was invaluable to my development as a scientist. Your dedication to producing high-quality research and focus on my development has been invaluable in the transformation of my thinking.

Second, I would like to extend my gratitude to Drs. Steffen Werner, Ronald Boring, and Mark Yama for agreeing to serve on my doctoral committee. Your feedback and support throughout the dissertation process helped me focus my research and better communicate my ideas.

Third, I would like to thank my previous teachers and mentors, including Dr. Brian Dyre, for the continued support and your belief in me. Without the investment of your time and effort, I certainly could not have reached this point.

Finally, I would like to thank all my colleagues and fellow students I have had the pleasure of working with throughout my years as a student.

Dedication

I am thankful for my family for motivating me through my journey as a doctoral student. I dedicate this work to my wife and parents. Thank you, Janine, for taking this incredible journey with me. Thank you, mom and dad, for always supporting my goals.

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Chapter 1 : Introduction

Unintentional injury places a significant burden on society. In the United States, unintentional injury is the leading cause of death for individuals between the ages of 1 and 44 and the third leading cause of death across the lifespan (WISQARS, 2021). An additional 28 million non-fatal unintentional injuries were also reported in 2017 (WISQARS, 2021). The cost of unintentional injury is also high, with an estimated $396 billion being spent on lifetime medical and work loss expenses in 2019 (C. Peterson et al., 2021). Overall, unintentional injury constitutes a costly and prevalent cause of mortality. Not surprisingly, a large body of research has focused on the etiology and prevention of unintentional injury.

Research examining the etiology and prevention of unintentional injury is broad and varied. Research can focus on a type of injury, such as traumatic brain injuries (Shen et al., 2020), modes of injury, such as pedestrian injury (Davis & Barton, 2017), risk factors leading to injuries, such as inhibitory control (Barton & Schwebel, 2007a), or even perceptual factors related to injury, such as audition and vision (Pugliese et al., 2020). A large portion of injury research taking an ecological approach has focused on the psychological, behavioral, and environmental risk factors associated with unintentional injury (Allegrante et al., 2010). Similar to the likelihood of contracting a disease, specific injuries have a particular set of risk factors increasing an individual’s susceptibility to injury.

Researchers have identified a plethora of risk factors for various injury risk behaviors. Sets of risk factors have been identified for bike injuries (Chihak et al., 2014), pedestrian injury (Barton, Ulrich, & Lew, 2012; Morrongiello et al., 2016), and unintentional child injury (Barton & Schwebel, 2007b; Morrongiello & Barton, 2009). Child injury is one area where antecedents have been extensively examined for various injuries. For example, some risk factors identified for child pedestrian injury include demographic characteristics such as gender (Barton & Schwebel, 2007a) and intrapersonal factors such as temperament and inhibitory control (Schwebel & Plumert, 1999). Overall, a wide variety of factors predictive of risk behaviors have been identified and explored

In addition to examining collections of risk factors, behavioral scientists also apply various models and theories to examine unintentional injury. The Risk Appraisal Framework, the Health Belief Model, Social Learning Theory, Theory of Planned Behavior, and others have been applied to the problem of injury (Barton et al., 2021; Gielen & Sleet, 2003; Sleet et al., 2010; Trifiletti et al., 2005). For example, the Theory of Planned Behavior examines the intention to engage in a given behavior by challenging subjective norms, attitudes, and perceived level of behavioral control (Sleet, Diekman, et al., 2010). In the field of injury prevention, the theory of planned behavior has been applied to topics such as seatbelt usage (Şimşekoğlu & Lajunen, 2008), driving violations (Forward, 2009), and pedestrian safety (Barton et al., 2016). In one study by Barton, Kologi, and Siron (2016), perceived behavioral control and attitudes were most predictive of behavioral intention to cross a street while distracted. Even with the wide variety of models applied to the problem of injury, few models originated specifically to study injury, and research remains largely atheoretical (Barton et al., 2021; Schwebel & Barton, 2005; Wallander, 1992).

Despite our growing understanding of injury etiology and the applied nature of the problem, much is left to explore. One unanswered question is why the same risk behavior will result in an injury in some instances but no injury in others (L. Peterson et al., 1987). In other words, how does a risk behavior become an injury? Further, how can we better predict an impending injury? What is certain, unintentional injuries are an undesired outcome. To this end, the concept of human error can help illuminate when a risk behavior transitions into an injury. The unintended result of an error does not always result in an unintentional injury, but an unintentional injury almost always includes some aspect of human error. Identifying where and how human errors occur can enhance the scientific understanding of injury etiology and help design more effective injury prevention programs.

The remainder of the introduction comprises four sections. The first section explores the concept of human error in a simplified 3-part model, including human fallibility, context, and barriers. The second reviews the application of human error regarding the conceptualization of accidents. The third investigates how the study of human error can enrich the study of unintentional injury. Finally, the last section of the introduction focuses on the aims and hypotheses of two studies examining the application of human error principles to better understand injury.

Human Error

Simply put, human error is when some action has gone wrong and may lead to an unintended consequence (Hollnagel, 2007). For instance, take someone intending to reverse out of a parking spot but putting the car in drive instead. Depending on the physical environment, this error could result in a minor consequence, like driving onto grass, or a significant consequence, like driving through a dining establishment window. Either way, the outcome is unintended, but context decides the impact of the action. Notice in the presented example the error is in an action the driver did not intend rather than in the intention itself. The intention was to put the car in reverse, but the action was flawed, resulting in an error.

An error can also occur when an action goes perfectly, but the intended action results in an unintended outcome. For instance, on March 27th, 1977, two Boeing 747s collided on a runway at Tenerife, Canary Islands, resulting in the worst accident in aviation history (Cistone, 2014). The planes collided while one plane attempted to take off, and the other was taxiing to their required runway. Each pilot performed the action they intended to complete, but the outcome was unintended. Some analyses identify a miscommunication between air traffic control and the airplane pilot attempting to take off as the potential critical error (Salmon et al., 2011). Still, in the Tenerife accident, the pilots performed the intended actions correctly, but the intention was wrong.

Identifying errors is only part of the problem, understanding the causes is arguably more important. By understanding errors, we can better predict and prevent when errors might occur. One framework breaks error into the variability of three components: human fallibility, context, and barriers (Sharit, 2012). Through the interplay between each element, human fallibility, context, and barriers, actions can result in a range of unintended and intended outcomes. Specifically, an error results from the interaction between variability in human fallibility and variability in context, where barriers can interact with behavior in various ways. Barriers can physically prevent behaviors, redirect behaviors, elicit behaviors, or interact with the consequences of behaviors by nullifying the potential unintended outcomes (Hollnagel, 2014; Reason, 1990).

Variability in Human Fallibility

The concept of human fallibility refers to the constraints of human-environment interaction created by human limitations. One way human fallibility could be conceptualized is through the functional limitations and tendencies of a human's sensory, cognitive, and motor systems (Sharit, 2012). The eye needs a certain amount of light to see. Working memory can only manipulate a finite amount of information at a given time, and controlled movement can only be steady. For instance, there is a certain threshold in which humans can discriminate between specific spatial frequencies (Georgeson & Sullivan, 1975). If a human must interact with a system where the discrimination of spatial frequency regularly moves outside of typical thresholds, the human will be unable to complete the task effectively.

The model of human information processing provides a helpful lens to understand human fallibility. The model of human information processing examines the process in which humans perceptually encode, process, and then respond to information in their environment (Wickens & Carswell, 2012). Understanding how humans handle information enables examining and predicting how environmental demands might overwhelm someone.

The general model of information processing conceptualizes received information as beginning with perceptual encoding, moving into central processing, and ending with some sort of response (Wickens, Hollands, Banbury, & Parasuraman, 2016). Perceptual encoding is the process in which some of the information sensed from the environment is perceived or consciously recognized by the individual. Any information perceived by an individual is then passed into the central processing network, where working memory and long-term memory handle the perceived information. In this case, working memory acts as the conscious platform for perceived information, and long-term memory acts as a reference system (Wickens & Carswell, 2012). Working memory is also responsible for manipulating information called from long-term memory, evaluation, decision making, and planning (Evans, 2008). Following working memory, a response is selected and then executed. Throughout the information processing model, attentional resources are selectively applied from the point something is sensed through response execution.

Understanding how humans process information and the limitations of the information processing system make the concept of human fallibility clearer. Take, for example, the attentional and long-term memory subsystems. Humans are often in a forced state of cognitive underspecification or in a state where information is incomplete, and humans are forced to fill in unknowns (Reason, 1990). When in a state of cognitive underspecification, attentional and long-term memory systems rely on top-down processing or previous experience to fill in the missing information (Connor et al., 2004). Depending on top-down processing can impact selective attention (Barton, 2006), visual search (Wolfe, 2010), and decision making (Klein, 2008). At any given moment, underspecified environments are activating long-term memory systems, creating expectancy, and enabling the potential for errors.

Working memory plays a pivotal role in understanding human error and impacts various activities. Each stage of information processing has the potential for a menagerie of potential errors but few impact errors as much as working memory. Working memory has multiple functions and links to errors in detection, planning, sensemaking, and decision making (Whaley et al., 2016). For example, working memory has been associated with performance in situation awareness (Gugerty & Tirre, 2000), vigilance tasks (Helton & Russell, 2011), prospective memory (Dodhia & Dismukes, 2009), and decision making (Klein, 2008). Working memory has also been associated with pedestrian injury and inefficient visual search (Kovesdi & Barton, 2013).

Human fallibility is an essential concept within the study of human error. Understanding the limitations of human ability, both physically and cognitively, allows for safer and more efficient designs. Also, understanding how humans are fallible makes the identification and analysis of human error much more accessible. By identifying exactly how human fallibility contributed to an incident of human error, the components of the context that exceeded the human’s capabilities can be identified.

Variability in Context

Context is difficult to define as all available information characterizing a given situation is included. Context includes information relating to people, places, and objects within a situation and the dynamic interactions between these entities (Dekker, 2006; Dey, 2001). Some examples of contextual information include the immediate environments design, social factors, individual differences, and previous training, just to name a few. The dynamic interactions between human actions and contextual factors make context even more challenging to map.

Human error is an emergent property of the interaction between the variability in human action and context (Hollnagel, 2007). Context not only outlines and defines human actions, but context also plays a crucial role in the emergence of human error. Context is a dynamic field constantly requiring humans to adjust and calibrate to achieve identified goals. However, the process of calibrating is far from straightforward, as the context and the calibration process have built-in variability. To make matters more complex, context and human activity interact in potentially unexpected ways.

The concept of Performance-Shaping Factors (PSFs) is one way some accident/error models operationalize context. Performance-Shaping Factors (PSFs) are all the contextual factors that can impact human performance (Lee et al., 2011). A PSFs impact does not necessarily need to be negative and can also lead to improved performance. Time pressure is an example PSF. If a situation offers more than enough time for an individual to complete a task, performance might be improved. On the other hand, if a situation does not provide sufficient time, performance might be degraded to the point of an error.

Many accident analysis and error models use PSFs, but even if models share some PSFs, most models use unique PSFs. PSF sets across accident models vary in structure, use, and specific PSFs (Kirwan, 1998; Salmon et al., 2011). Some of the differences are due to domain-specific models, such as the Technique for the Retrospective and Predictive Analysis of Cognitive Errors (TRACEr). TRACEr, initially designed for predicting error in air traffic control, includes the unique PSF of traffic complexity (Shorrock & Kirwan, 2002). Other differences emerge from the way PSFs are meant to be applied. For example, models such as the Technique for Human Error Rate Prediction (THERP) and The Human Error Assessment and Reduction Technique (HEART) both apply specific probabilistic impacts on human error if a particular PSF is present (Boring, 2012; Kim et al., 2018; Williams, 1988).

On the other hand, other models such as the Cognitive Reliability and Analysis Method (CREAM) does not directly apply a specific probability of failure if one particular PSF is present but instead places a qualitative impact on performance (Hollnagel, 1998). The differences in PSFs across models makes comparing and interpreting the findings using specific methods difficult without being an expert in various analysis method. Furthermore, the lack of standardization makes an unwieldy list of PSFs challenging to support with empirical research.

Recently the breadth of methods using PSFs has sparked interest in creating a standardized list of PSFs applicable across a wide variety of domains. One such standardization introduced a data-informed PSF hierarchy capable of being mapped onto several of the most popular error models (Groth & Mosleh, 2012). Heavily inspired by the nuclear power industry, this hierarchical model of PSFs uses a combination of previous sets of PSFs and data gathered from research surrounding the Information, Decision, and Action in crew Context (IDAC) to inform the structure and inclusion of the PSFs (see table 1.1). The PIF hierarchy outlined by Groth and Mosleh (2012) offers a comprehensive list of PSF and allows researchers to examine each PSF's impacts at a more refined level. The PSF hierarchy has also been linked with cognitive mechanisms for a comprehensive link between cognitive failures and PSFs in the nuclear power industry (Whaley et al., 2016). Despite being conceptualized in the nuclear power industry, a link between high-level cognitive processes and contextual PSFs provides a good framework for researching error in any situation.

Organization-based	Team-based	Person-based	Situation/stressor-based	Machine-based
Training program	**Communication**	**Attention**	**External environment**	**Human-system interface**
Availability	Availability	To task	**Conditioning events**	Input
Quality	Quality	To surroundings	**Task load**	Output
Corrective action program	**Direct supervision**	**Physical and psychological abilities**	**Time load**	**System response**
Availability	Leadership	Alertness	**Other loads**	
Quality	**Team coordination**	Fatigue	Non-task	
Other programs	**Team cohesion**	Impairment	Passive information	
Availability	**Role awareness**	Sensory limits	**Task complexity**	
Quality		Physical attributes	Cognitive	
Safety culture		Other	Execution	
Management activities		**Knowledge/experience**	**Stress**	
Staffing		**Skills**	**Perceived situation**	
Scheduling		**Bias**	Severity	
Workplace adequacy		**Familiarity with situation**	Urgency	
Resources		**Morale/motivation/attitude**	**Perceived decision**	
Procedures			Responsibility	
Availability			Impact	
Quality			*Personal*	
Tools			*Plant*	
Availability			*Society*	
Quality				
Necessary information				
Availability				
Quality				

Table 1.1. PSF hierarchy adapted from Groth and Mosleh (2012).

In all, context sets the stage for any attribution of human error. As humans attempt to calibrate their behavior to a dynamic context, their predictions may fail to prepare for unexpected changes previous experience does not consider. The state of cognitive underspecification requires the interaction between context and the cognitive-perceptual structures an individual brings to a context. Human actions stem from context, and context allows for value judgments to be applied to the outcomes of action (Dekker, 2005). The interaction between human fallibility and context is more important than either component alone.

Variability in Barriers

Barriers are another vital component in the study of human error. Barriers are mechanisms within a context possessing the ability to nullify or lessen potentially hazardous outcomes possibly caused by human error (Hollnagel, 2004; Reason, 1990; Reason, Hollnagel, & Paries, 2006). However, understanding how barriers impact error can be complex. The insertion of barriers into a context inherently alters how human fallibility, context, and barriers interact. By introducing a new barrier to a context, both the context and how human fallibility presents itself are changed, changing the interaction.

Barriers are not only physical mechanisms possessing the ability to prevent error but also include less tangible mechanisms meant to curve error. For example, the social norms of a group could act as a powerful barrier against performing an action like stealing. Hollnagel (2004) described four ways humans interact with barriers: physical, functional, symbolic, and incorporeal (see table 1.2).

Barrier Function	Example
Physical Barrier	
Containing or protecting/ Prevent transporting something from the present location (e.g., release) or into the present location (penetration)	Walls, doors, buildings, restricted physical access, railings, fences, filters, containers, tanks, valves, rectifiers
Restraining or preventing movement or transportation of mass or energy	Safety belts, harnesses, fences, cages, restricted physical movements, spatial distance (gulfs, gaps)
Keeping together; cohesion, resilience, indestructibility	Components that do not break or fracture easily (e.g., safety glasses)
Separating, protecting, blocking	Crumble zones, scrubbers, filters
Functional Barrier	
Preventing movement or action (mechanical, hard)	Locks, equipment alignment, physical interlocking, equipment match
Preventing movement or action (logical, soft)	Passwords, entry codes, action sequences, preconditions, physiological matching (e.g., iris, fingerprint, alcohol level)
Hindering or impeding actions (spatial-temporal)	Distance (too far for a single person to reach), persistence (deadman button), delays, synchronization
Dampening, attenuation	Active noise reduction, active suspension
Dissipating energy, quenching, extinguishing	Air bags, sprinklers
Symbolic Barriers	
Countering, preventing, or thwarting actions	Coding of functions (e.g., by color, shape, spatial layout), demarcations, labels, and (static) warnings (facilitating correct actions may be as effective as countering incorrect ones)
Regulating actions	Instructions, procedures, precautions/conditions, dialogues
Indicating system status	Signs (e.g., traffic signs), signals (visual, auditory), warnings, alarms
Permission or authorization (or the lack thereof)	Work permit, work order
Communication, interpersonal dependency	Clearance, approval (on-line or off-line) in the sense that the lack of clearance, etc., is a barrier
Incorporeal Barriers	
Complying, conforming to	Self-restraint, ethical norms, morals, social or group pressure
Prescribing: rules, laws, guidelines, prohibitions	Rules, restrictions, laws (all either conditional or unconditional)

Table 1.2. A barrier classification adapted from Sharit(2012) and Hollnagel (2004).

Physical barriers are physical objects that limit movement and include objects like walls, safety belts, and safety rails. Functional barriers are objects in the environment capable of preventing a typical function of something through limiting behaviors and include locks, passwords, and distance. Symbolic barriers are symbolic objects or ideas capable of limiting action and include procedures, signs, and alarms. Finally, incorporeal barriers are intangible objects capable of limiting behaviors, including self-restraint, morals, or laws.

Barriers remain an essential part of the study of human error. Barriers represent contextual manipulations meant to reduce the number of errors or nullify their effect. Some forms of accident analysis and human error investigation focus solely on how accidents arise from a cluster of failed barriers (Reason et al., 2006; Wiegmann & Shappell, 2001). The focus of some human error methods on barriers is not surprising as barriers are some of the most corporeal components in the concept of human error. The introduction of a seat belt is much easier to conceptualize than how the working memory system interacts with the perceptual system interact with traffic injuries.

System Level Analyses

Systems level thinking in accident analysis is the modern standard of examining major accidents and incidences of error. A classic interpretation of error examines the sharp end of error or the individual most closely associated with an unintended outcome (Vuorio et al., 2014). However, more modern interpretations of human error examine the blunt end of error or the entire system in which the error occurred (Cook & Woods, 1994). In other words, modern analyses of error examine how unintended outcomes emerge from latent interactions within a system potentially originating far from the person who made the error. For example, HFACS, Accimap, FRAM, and the Systems Theoretic Accident Modelling and Process Model (STAMP) all examine the entire system during both prospective and retrospective analyses of error (Hollnagel, 2012; Leveson, 2004, 2017; Rasmussen, 1997; Rasmussen & Svedung, 2000; Reason, 1990; Wiegmann & Shappell, 2001).

Numerous methods exist to model an accident system, but the Swiss Cheese Model (SCM) is arguably one of the best-known conceptualizations. According to the SCM, accidents emerge from the interaction between latent failures within a system and unsafe acts (Reason, 1990). To illustrate, one could imagine latent and active failures as the holes in slices of swiss cheese. Accidents only occur when, after you stack the slices of swiss cheese, the holes line up in a way in which one can place one’s finger through the stack (see Figure 1.1). Reason identified several levels at which latent failures can exist: the organizational level, the supervisory level, precursors to unsafe acts, and barriers (Reason et al., 2006). Beyond latent failures, active failures, or errors, must also be present for an accident to occur (Sheridan, 2008). The conceptualization of accidents as a rare outcome due to a perfect storm of contextual factors, barriers, and human error is a concept permeating many modern accident analysis techniques.

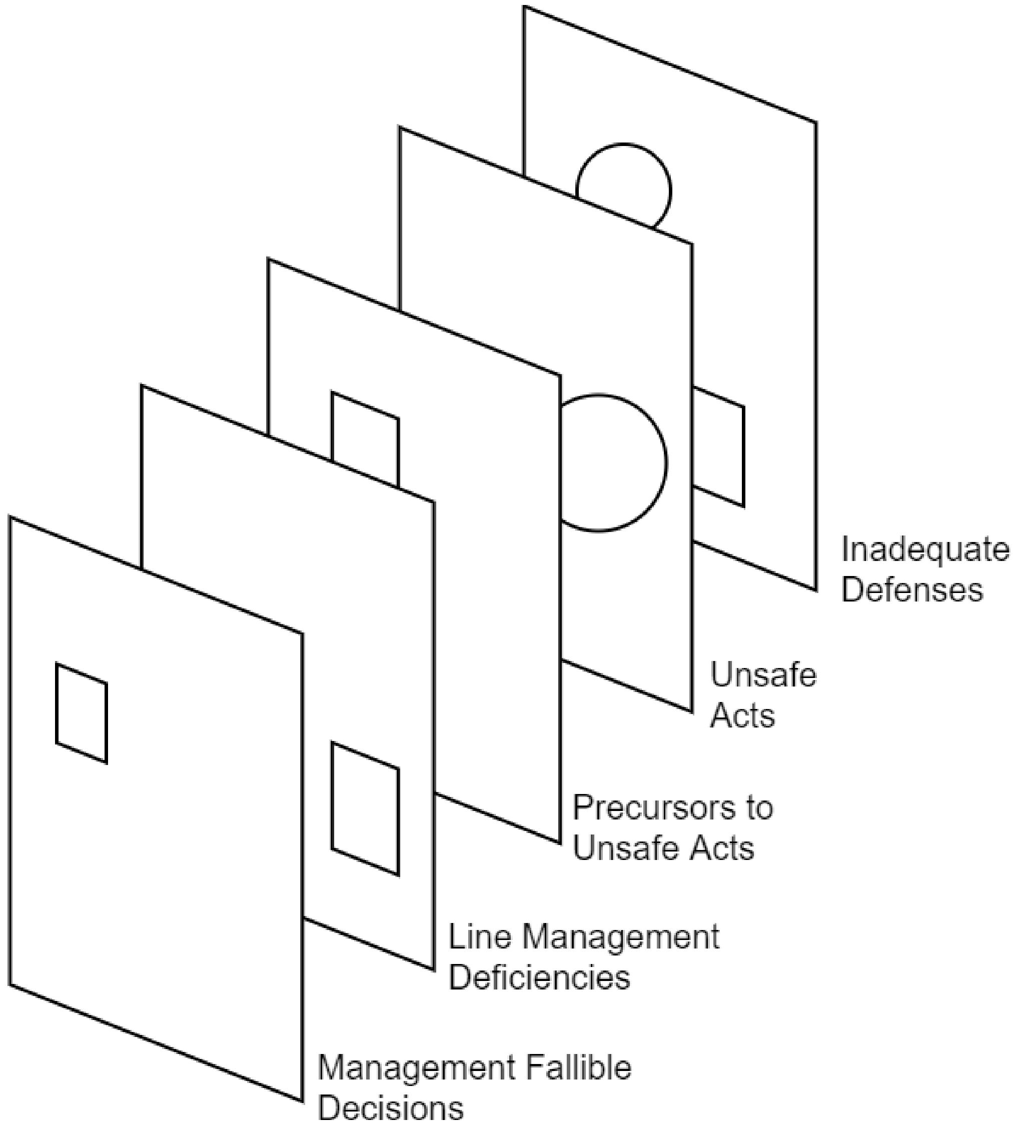

Figure 1.1 The Swiss Cheese Model. Latent failures are represented by rectangular holes in layers. Active failures are represented by circular holes in layers. Each layer can contain latent failures, active failures, or both. When the holes of each layer align, an accident can occur. Adapted from (Reason, 1990)

The SCM serves as an excellent conceptual description of how accidents occur and significantly impacts accident analysis techniques. For instance, HFACS is a modified version of the SCM used initially to examine aviation accidents but now applied to various transportation incidents (Reinach & Viale, 2006; Shappell et al., 2007; Wiegmann & Shappell, 2001). HFACS conceptualizes accidents and errors the same as the SCM but also includes easy to apply taxonomies for latent and active failures across four levels of a system: organizational influences, unsafe supervision, preconditions for unsafe acts, and unsafe acts (Shappell et al., 2007). The low incidence of accidents in the aviation industry could be credited to good use of retrospective, system-level accident analyses (Wiegmann & Shappell, 2003).

The Space Shuttle Challenger disaster in 1986 can be used to illustrate how HFACS can be implemented. On January 28th, 1986, the Space Shuttle Challenger was scheduled to take off for a satellite deployment mission (Rogers, 1986). However, a little over a minute after the space shuttle Challenger was launched by NASA, the shuttle disintegrated, and all seven crew members died. Investigations after the disaster eventually discovered a failed O-ring seal at a crucial joint on the right rocket booster. Still, a closer examination of the incident illustrates an alignment of latent and active failures (Altabbakh, 2013). Organizationally, the budget was a significant constraint upon NASA at the time of the Challenger incident, the turnover rate for management was relatively high, and communication throughout the company was poor (Kerzner, 2013). Supervisory violations regarding safety practices were common due to external pressure to launch the rocket on schedule. Preconditions for unsafe acts included poor weather conditions, which included ice on the launch pad, the failure of the O-ring to seal properly was related to the weather, and management applied significant pressure on the crew to launch on schedule. If one of the latent failures was not present, the Space Shuttle Challenger disaster might have been avoided.

Macrocognition and Human Error

One novel way of looking at human error is by applying PSFs at the macrocognitive level. The high-level idea is to predict and prevent error cross-contextually by understanding how PSFs impact typical behaviors (Whaley et al., 2016; Whaley, Hendrickson, & Boring, 2012). However, because macrocognition is not a widely-known concept outside the field of human factors, I will briefly discuss macrocognition before discussing the application of PSFs to the macrocognitive level.

Macrocognition comprises all mental steps and functions required to complete a real-world task in a natural environment (Klein et al., 2003). Instead of focusing on a specific cognitive component, like working memory or long-term memory, macrocognition encompasses cross-contextual functions potentially encompassing multiple cognitive components (Klein & Wright, 2016). Take decision-making as an example. Decision-making relies on numerous cognitive components in the information processing model. Making a decision depends on perceptual systems, attention, working memory, long-term memory, and action working together. Studying working memory alone to better understand decision-making can help understand decision-making but may never illuminate the complexities of the cognitive interactions making expert decision-making possible.

Macrocognitive models include a mixture of functions and processes. The classic model proposed by Klein et al. (2003) contains naturalistic decision-making, sensemaking, planning, coordinating, problem detection, and adapting/replanning. Other models include other functions and processes based on their focus, such as group collaboration (Letsky et al., 2007) or the nuclear power industry (Whaley et al., 2016). In all, the specific components included in a macrocognitive model will depend on the end goal of the model. Still, the purpose of macrocognitive models is always the same, to examine cognition as groups of mechanisms work together in natural settings (Klein et al., 2003). The model is designed to flex with need and research.

Recently, PSFs have been applied at the macrocognitive level to better understand the relevant causes and contributors to failure in cognition (Whaley, Hendrickson, & Boring, 2012). Specifically, macrocognitive functions relevant in the nuclear power industry have been examined in terms of what causes them to fail, the cognitive mechanisms associated with that failure, and the PSFs that impact those cognitive mechanisms (Whaley, Hendrickson, & Boring, 2012; Whaley, Hendrickson, Boring, et al., 2012). For example, specific PSFs impact the performance of a cognitive mechanism, like working memory, a failure in working memory can lead to incorrect pattern matching, and the incorrect pattern matching can lead to a failure in decision making. The cognitive framework proposed by Whaley et al. (2016) includes detecting/noticing, sensemaking/understanding, decision making, action, and team coordination at the macrocognitive level and a host of failures, cognitive mechanisms, and PSFs.

The strength of this model is the applicability across tasks. Many tasks share different levels of similar macrocognitive processes, and focusing on the macrocognitive level allows research to cross task-specific research. For example, diagnosing an alarm and detecting cancerous cells in an x-ray require several of the same macrocognitive functions, detecting, and understanding. Understanding the types of PSFs impacting detection or understanding can help reduce error in both tasks. Though this thinking has not expanded much outside of the nuclear power industry, the cross-contextual reach of understanding what leads to macrocognitive failures is immense.

Injury Risk and Human Error

Preventing error is preventing unintentional injury. Theoretical frameworks from the study of human error provide applicable concepts capable of reducing and preventing unintentional injury. Injury research has found various risk factors for specific injury types, but the contexts and nature of the injury are potentially limitless. Because of the potentially unlimited causes and types of injury, researchers may gain more insight into the causes of an injury by examining the potential errors associated with a context. By focusing on predicting human error using the human fallibility, context, and barriers framework, researchers can predict and stop the injury by preventing unintentional outcomes.

Take, for example, a hypothetical child bicycle accident. From an injury risk perspective alone, one might identify low inhibitory control, age, gender, and aggression as predictive of poor route selection and injury (Marsh et al., 2000; Stevens et al., 2013). However, there is no way to tell when an injury might occur, just the characteristics of a child more likely to be injured or the ways one can prevent injury by redesigning the task. By examining human fallibility, context, and barriers, we can predict the specific potential for injury and even redesign the task to prevent injuries.

In line with the systems approach, examining each element together will provide a clearer picture of injury risk. First, human fallibility and context come together to describe how the child might fail to meet the requirements for the situation. Specific contexts exacerbate individual characteristics, making the two constructs difficult to separate. To examine the two together from a holistic perspective, the application of PSFs can identify targets in particular contexts that increase error rate and injury rate.

Task complexity, for example, is associated with a degraded performance in primary tasks, in this case riding a bike (Liu & Li, 2012). Traffic flow of a specific area, traffic frequency, the child's age, experience the child has riding bikes, the characteristics of the bike, and weather can all immediately impact task complexity. For example, traffic flow increases the number of things in the environment for the child to keep track of and the visual search capabilities of a child are already lower than an adult's (Barton, Ulrich, & Lyday, 2012). From identifying potential for failure caused by the human-context interaction, barriers can be examined to minimize the specific types of dangers. For example, controlling the location, a child rides their bike to remove the impact of traffic flow. Understanding the impact of even one PSF can begin to help illuminate the likelihood of an injury at any given time and help identify the types of barriers needed to prevent a severe injury.

Cross-Contextual Behaviors and Injury Prevention

One way to better understand injury risk is by applying PSFs at the macrocognitive level. As a relatively new approach, the application of PSFs to macrocognitive processes has yet to expand much further than the nuclear power industry (Whaley et al., 2016). However, the approach has immense potential in the research and prevention of injury. To better make my point, I will first briefly discuss current injury research then elucidate how implementing a macrocognitive approach may prove helpful as an etiology and prevention tool.

Current research in unintentional injury is heavily siloed by the mechanisms and types of injury. Some research focuses on the mechanisms of injury such as dog bites, pedestrian injury, playground injury, occupational injury (Barton et al., 2016b; Guerin & Sleet, 2020; Meints & De Keuster, 2009; Schwebel, 2006). Other research focuses on the types of injuries such as traumatic brain injury, abdominal injuries, or back injuries (Cassidy et al., 2004; Michaud et al., 2021; Muggenthaler et al., 2017). None of this is to say research on unintentional injury is ineffective. Research on injury etiology and prevention does an excellent job of finding the antecedents to injury and subsequently preventing them. However, by taking a step back from the specific injury domain and focusing on cross-contextual behavior, we can identify a set of factors at a high enough level to impact multiple injury types.

Implementing a macrocognitive-inspired approach provides a ready-made mechanism to understand injury from a cross-contextual perspective. Research necessarily unifies by focusing on functions performed by humans across the various injury domains. For example, one of the most common injury causes in the U.S. is unintentional stuck by/ or against

(WISQARS, 2021). Research focusing on specific scenarios where one might be struck by an object, such as a pedestrian or sports setting, is an effective way to reduce injury in that particular context. However, examining cross-contextual behaviors relevant for being struck by an object can provide insight into various injuries where an object strikes individuals. At the cross-contextual level, research might focus on the PSFs that impact the detection of potentially dangerous objects, the tracking of multiple objects, or the actions taken to avoid the impact.

Aims and Hypotheses

My goal was to integrate systems level accident analysis and the concept of PSFs in order to enhance understanding of injury risk behavior. Specifically, I hope to apply PSFs to an injury-relevant cross-contextual behavior to better predict and prevent injury outside of specific contexts. Across two studies, I explored the impact of a group of task-relevant PSFs on performance and error/injury rate at the macrocognitive level. First, I examined the relative impact of task complexity, time pressure, psychological abilities (non-verbal memory span), and sensory limitations on performance and error rate in an abstract multiple object-tracking (MOT) task. In the second study, I expanded the first study's findings by examining the relative impact of the same PSFs on performance and injury rate in an applied pedestrian crossing task. Both studies examined tracking of multiple objects, an injury-relevant cross-contextual behavior.

Both studies share a set of common hypotheses. I expected each PSF to result in degraded performance on experimental tasks. As task complexity, time pressure, and sensory limitations increased, performance was expected to degrade. I also expected the increase in task complexity, time pressure, and sensory limitations to result in an increased error rate in the abstract MOT task and an increased injury rate in the pedestrian task. Additionally, I expected individual differences in working memory psychological ability would also predict performance on experimental tasks and an increased error rate. Participants with a lower non-verbal memory span are expected to have lower performance on experimental tasks and an increased likelihood of injury/error.

Chapter 2 : Methods

Experiment 1

Sample

Previous research indicates large effect sizes for time pressure ($\eta_p^2 = 0.20$) (Irwin et al., 2013), task complexity ($R = 0.65$) (Maynard & Hakel, 1997), and sensory limitations ($\eta_p^2 = 0.36$) (Pugliese et al., 2020). Based on those effect sizes, a power analysis indicated a required sample of 50 participants to achieve a power of 0.8. Seventy-five adults participated in the study but nine were excluded from the final data analysis due to incomplete or irregular data. For example, several participants were excluded for not following task directions or admitting to guessing on MOT trials. Sixty-six adults aged 18-36 years (*M* = 20.26, *SD* = 3.24, 26 males) were included in the final data analysis. Of the participants who completed the experiment, 83% identified as Caucasian, 3% identified as Native American, 3% identified as Asian, and 11% identified as other. Forty-three participants reported wearing corrective lenses, but no participants reported having trouble seeing the computer screen. No participants reported having problems with auditory perception.

Measures

Demographic questionnaire. No demographic hypotheses were examined, but general demographic information was collected to understand our sample better. Participants reported age, sex, visual or auditory deficits, and previous injury history. Previous injury history includes any medically attended unintentional injury sustained within the year.

Non-verbal working memory span. The Corsi Block Task (CBT) measured non-verbal working memory. The CBT has been used extensively in clinical and nonclinical settings to measure non-verbal working memory (Arce & McMullen, 2021; Berch et al., 1998; Gupta et al., 2019). Our CBT was a digital version of the CBT presented in previous research (Pagulayan et al., 2006). No significant differences have been found in visual memory span between the traditionally physical task and an analog computer task (Robinson & Brewer, 2016).

The CBT implemented in this study consists of 9 purple 3-dimensional blocks arranged on a dark blue background and was previously used in Davis & Barton (2021). The pointer-object was modeled after a pencil to stay as close to the physical task as possible and retain the motor priming associated with moving between blocks (Davis & Barton, 2021; Pagulayan et al., 2006). See figure 2.1 for an image of the task. The CBT was presented on a 23-inch 1080p resolution monitor, and participants were given four practice trials with two-block sequences to ensure they understood the task. Participants were required to remember the sequence in which a preset number of boxes were selected and subsequently tap the boxes in the same order. Boxes were selected by the pointer at a one box per second rate, and increased difficulty as the trials progressed (Pagulayan et al., 2006). Level of difficulty is defined as the number of blocks included in each sequence progressing from level 3 to level 9 (Berch et al., 1998). Each level consisted of 3 randomly generated standardized sequences and did not include repetitions of the same block in the same trial. In line with previous research, accuracy was used as the primary score of working memory (Berch et al., 1998; Pagulayan et al., 2006; Rowe et al., 2009). Accuracy is defined as the ratio of total correct responses from the total possible correct responses.

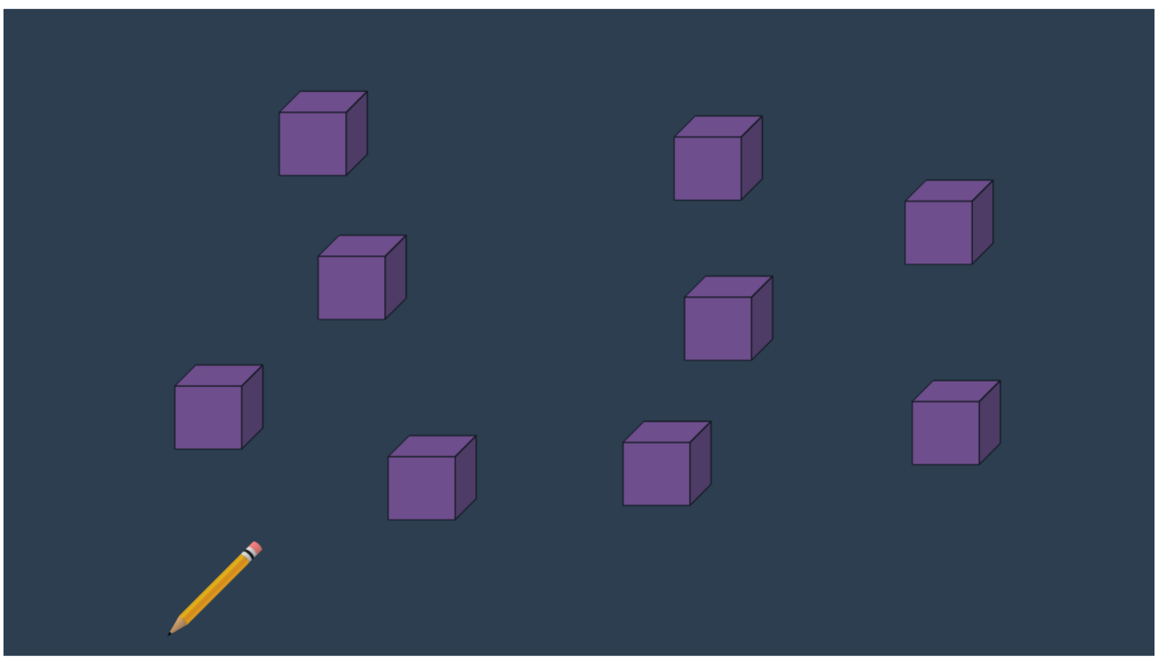

Figure 2.1 The Corsi Block Task used to test participant's nonverbal working memory span. This task was also used in Davis & Barton 2021.

Multiple object-tracking task. Participants were asked to participate in a digital multiple object-tracking (MOT) task. In a typical laboratory-based MOT, participants are asked to track several objects as they move randomly among a larger set of independent objects (Luo et al., 2021; Pylyshyn, 2004; Trick et al., 2005). The MOT used in this study was created by me in the Unity gaming engine and guided by Trick et al., 2005. Participants were tasked with keeping track of several blue circles (targets) as they moved around a rectangular black tracking area with other non-target blue circles (distractors). Participants sat 50 cm (20 in) away from the computer screen, and the tracking area occupied 21.24° X 36.86° visual angle (19.06 cm x 33.86 cm) on the computer screen. The targets and distractors, 10 in total, had diameters of 2° and were repelled by the borders of the tracking area. Targets and distractors could occlude one another. See figure 2.2 for an image of the MOT used for this study.

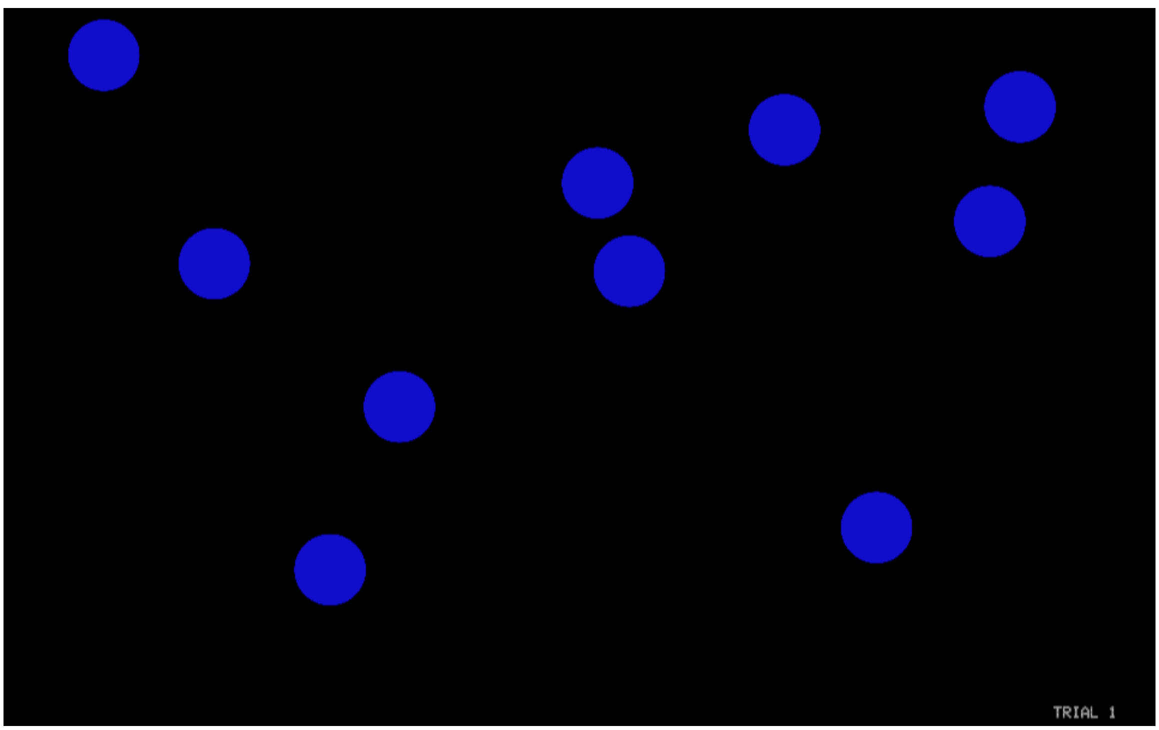

Figure 2.2 The abstract multiple object tracking task used in study 1.

Each MOT trial consisted of 4 stages. The first stage consists of the initialization of the targets and distractors. Participants were required to press the space bar when they felt ready to initialize the next trial. The second stage consisted of the target acquisition stage. Over 4.5 seconds, 2-5 targets alternated between blue and green at 500ms per color to indicate which circles the participant needed to track. The 4.5 second target acquisition phase ended with a 500ms pause. Stage 3 was the tracking phase where all items, targets, and distractors, moved randomly and independently for 10 seconds. The final stage consisted of identifying the targets the participant managed to track by clicking on the targets using a computer mouse. During the identification stage, participants were instructed only to select a ball as a target if they felt sure they were correct in its identification to reduce the likelihood of random guessing.

After the initial instructions, participants were given eight practice trials: 2 at each level of targets with 100% salience and 1x speed. Seventy-two randomized trials followed the practice trials with varying levels of the following factors: task complexity (4 levels as the number of targets: 2, 3, 4, or 5), time pressure (3 levels by the speed of balls: 1x [2.25°/s], 2x [4.5°/s], 3x[6.75°/s]), and sensory limitations (6 levels of salience: 100%, 80%, 60%, 40%, 20%, 10%). Each factor was manipulated within the typical range used in MOT research. For example, 2-5 targets and movement speeds between 0°/s- 9°/s are typical manipulations in MOT trials (Meyerhoff et al., 2017; Pylyshyn, 2004; Trick et al., 2005). On the other hand, salience, or surface features in general, do not have an extensive presence in the MOT literature (Meyerhoff et al., 2017; Papenmeier et al., 2014; Scholl et al., 2001). Participants were scored based on their accuracy (number of targets selected correctly/number of targets in the trial) and if they managed to track all the objects. The more objects a participant was able to keep track of, the better their score would be for that trial. For example, keeping track of 4 out of 5 balls would lead to a score of 80% accuracy and 3 out of 5 would lead to a score of 60% accuracy.

Time pressure, task complexity, and sensory limitations are PSFs included in the data-informed PSF hierarchy and present themselves in models such as HFACS (Wiegmann & Shappell, 2001, 2003). Time pressure was operationalized as the movement speed of objects. Time pressure effectively reduces the amount of time an individual has to process and act upon some stimuli. By conceptualizing time pressure as the speed of stimuli, the need to have set trial times is removed, and participants were able to participate in many more trials. Task complexity can be operationalized in many ways, but temporal demand, quantity, and action complexity were captured by increasing the number of targets (Liu & Li, 2012). Finally, rather than alter the sensory system of participants, the salience of stimuli was manipulated for a similar effect.

Procedures

The procedure comprised several steps after informed consent. First, the demographics questionnaire was administered. Second, the participants completed the Corsi Block Task. Finally, participants completed the multiple object-tracking task.

Analyses

Analyses proceeded in several steps. First, I screened the collected data irregular data at the participant level. Irregular data included participants that were flagged due to irregularities during data collection or data that was impacted by technical issues. Second, descriptive statistics were examined. Third, a targets (4) x speed (3) x salience (6) repeated measures factorial ANOVA was performed to examine the impact of time pressure, task complexity, and environmentally imposed sensory constraints on the safety time. Sphericity was checked for each main effect using Maulchy's test of sphericity. Where sphericity was violated, the Greenhouse-Geisser correction was used. Interactions were excluded from analyses to stay consistent with the originally stated hypotheses, and a large number of levels in factors make interpretation difficult. Fourth, because nonverbal working memory span was measured continuously, including the Corsi accuracy measure as a between-subject measure in the factorial ANOVA would have been inappropriate. Instead, a correlation was done to determine the relationship between nonverbal working memory span and multiple object-tracking accuracies for each participant. Finally, a set of logistic regressions using a generalized linear mixed-effect model (GLMM) procedure were performed to identify the relative impact of PSFs (Kim et al., 2015).

GLMM removes the statistical assumption of measurement independence required for a typical regression (Keith, 2019). A typical regression may increase the likelihood of significance for repeated measures due to the correlated residuals of each within-subjects measure (Galwey, 2014). Generalized linear mixed models were performed in two steps (Sommet & Morselli, 2017). The first step examined model tested for significant clustering effects for participant-level data. The second model includes all of the components hypothesized as predictors of error.

Experiment 2

Sample

Previous research indicates large effect sizes for time pressure ($\eta_p^2 = 0.20$) (Irwin et al., 2013), task complexity ($R = 0.65$) (Maynard & Hakel, 1997), and sensory limitations ($\eta_p^2 = 0.36$) (Pugliese et al., 2020). Based on those effect sizes, a power analysis indicated a required sample of 40 participants with a power of 0.8. The original sample consisted of 88 participants, but 7 were excluded from the final data analysis due to incomplete or abnormal data. For example, there were early connectivity issues with the virtual reality system. The final sample consisted of 81 participants aged 18-27 (*M* = 19.70, *SD* = 2.00, 23 males) recruited from the undergraduate population at the University of Idaho. Of the participants who completed the experiment, 76.5% identified as Caucasian, 2.5% identified as African American, 3.7% identified as Native American, 7.4% identified as Asian, and 9.9% identified as other. Forty participants reported wearing corrective lenses, but no participants reported having trouble seeing the computer screen or the VR simulation. No participants reported having known auditory issues. Finally, no participants reported ever having been struck by a vehicle, but 12 participants reported having known someone who has been.

Apparatuses

Virtual Environment. Stimuli presentation took place in a high-fidelity pedestrian crossing simulation. Previous research has validated the use of virtual reality simulators to examine pedestrian behavior (Deb et al., 2017; Schwebel et al., 2008). The simulation was presented using an HTC Vive Pro virtual reality head-mounted display (HMD). The Vive Pro has dual 3.5” AMOLED high definition displays (1440 x 1600 resolution per eye, 90 Hz refresh rate) and provides a 110-degree field of view. Besides presenting a high-fidelity display of a pedestrian crossing environment, the Vive Pro also supports real-time tracking of a user’s location in space over a 7m x 7m space.

Vive positioning was tracked using 2 Vive base stations angled down at approximately 30 degrees. Base stations were positioned facing each other on opposite corners of available lab space, approximately 5m apart and 2m high. Participants always stood in the middle of this area to ensure proper tracking of participants' movements. Furthermore, the Vive Pro was equipped with a wireless attachment. Previous research has found tracking accuracy for the Vive HMD to be about 1.5cm (Borrego et al., 2018).

The virtual environment was created using the Unity engine, game development software often used to create realistic simulations. The virtual environment was built using a combination of asset packages from Unity and custom-built C# scripts. Participants stood at the side of a three-lane one-way road (12m wide) in an urban area as if they were crossing the street. The crossing location in the urban environment consisted of storefronts, sidewalks, curbs, street signs, trees, and a park. The urban environment also had varying levels of fog introduced using the inbuilt physics and light engine included in the Unity software to limit visual stimuli. See figure 2.3 for an image of the crossing location as the participant saw.

Figure 2.3 The view of the pedestrian task looking straight across the street from the perspective of the participant.

Vehicle Stimuli. The virtual vehicle models consisted of a red four-door sedan used in previous research (Pugliese et al., 2020). Vehicles emitted realistic engine and tire noise.

Our vehicle sound library consists of stereo recordings used in previous work made using a tripod-mounted Edirol R-09HR digital field recorder placed on the side of the road while the vehicles drove passed approaching from the left (Davis & Barton, 2017; Pugliese et al., 2020; Ulrich et al., 2014). Vehicle sounds used in this study include a 2008 Toyota Camry used in previous pedestrian safety research (Davis et al., 2019). Sound stimuli were recorded at night on a clean road to isolate the sounds made by the vehicle.

Input Device. Participants used one of the two Vive controllers as an input device. Participants held the Vive controller in their dominant hand and were instructed to pull the controller's trigger using their index fingers when they felt they could safely cross the virtual road.

Measures

Demographic questionnaire. No demographic hypotheses were examined, but general demographic and previous injury data were collected to understand our sample better. Participants reported age, sex, visual deficits, auditory deficits, and prior experience with vehicle-pedestrian accidents (Pugliese et al., 2020). Specifically, participants reported if they had ever been struck by a vehicle, they had ever nearly been hit by a vehicle, and if they knew anyone ever hit by a vehicle.

Pedestrian Crossing Task. Participants were placed in the virtual environment via the HTC Vive Pro HMD and asked to decide when they would cross a 3-lane one-way road. Vehicles only approached participants from the left, as previous research has found no meaningful differences in pedestrian decision-making based on the directionality of approaching vehicles (Barton, Ulrich, & Lyday, 2012; Davis & Barton, 2017). Vehicles approached participants in constant streams. Participants were instructed to identify whenever they felt they could safely cross the road through the press of a trigger on the Vive controller. Participants never physically walked across the virtual road. Instead, the trigger press on the Vive controller spawned a blue avatar at the participant's position, which walked across the street at the average pedestrian walking speed of 1.46 m/s (4.79 ft/s) (Fitzpatrick et al., 2006). The use of an avatar provided feedback to participants in each trial and avoided the potential for dangerous maneuvers participants might make to avoid a collision. See figure 2.4 for an example of the avatar and figure 2.5 for an example stream of vehicles, both seen from a participant's perspective.

Figure 2.4 The view from a participant's perspective when the summon their avatar to cross the road for them. The avatar walked at 1.46 m/s, the average pedestrian walking speed (Fitzpatrick et al., 2006).

Figure 2.5 A stream of traffic as seen from the participant's point of view.

The pedestrian task consisted of a total of 45 randomized trials. Each trial contained varying levels of the following factors: task complexity (3 levels as the number of lanes: 1, 2, or 3), time pressure (3 levels by speed: 12mph, 25mph, 35mph), and sensory limitations (5 levels of fog: 100%, 80%, 60%, 40%, 20% visibility). Each trial comprised a stream of vehicles approaching participants from the left in 1, 2, or 3 lanes with varying fog and vehicle speed levels. Each stream of vehicles in a trial consisted of 21 vehicles per lane with 17 uncrossable gaps and 3 crossable gaps between vehicles randomly interspersed. We calculated the gap sizes by multiplying the minimum amount of time the avatar would need to cross through each vehicle gap by an uncrossable modifier (0.85) or a crossable modifier (1.15). A mixture of pilot testing and previous research done in our lab helped set the modifiers.

After the initial instructions, participants participated in 3 practice trials where they could practice crossing the road with their avatar as many times as they wanted through an endless stream of traffic. All practice trials had no fog and vehicles moving at 15mph in one, two, and three lanes, respectively. Participants were instructed to adjust their judgments to the avatar’s walking speed and let the researcher know when they were ready to move forward to the subsequent trial. Unlike practice trials, during experimental trials, participants were only able to cross the road once using their avatar and only after the first vehicle in the stream of traffic crossed their position. Participants had a mandatory 2-minute break every 16 trials.

Independent variables. The independent variables examined in this study are unique in the pedestrian literature. Of the three components manipulated (number of lanes, speed, and fog), only speed has a strong precedent in the literature. The speeds included in this study are considered typical road speeds and have been implemented in previous research (Davis et al., 2021; Pugliese et al., 2020). On the other hand, pedestrian literature does not commonly include the examination of visibility and lanes of traffic.

The visibility level for this study was controlled through the application of fog. Previous research has set fog lines at specific viewing distances to manipulate visibility (Davis & Barton, 2021). However, a set distance would not consider the vehicular distance required between a pedestrian and a vehicle to make a safe crossing. A 100m fog distance would impact crossing decisions for faster moving vehicles as a safe crossing would require a faster-moving vehicle to be further away. Instead, fog distances for this study were based on the spawning distance of vehicles and the minimum distance a vehicle would need to be for the participant to cross the road safely. One hundred percent visibility was defined as the fog line being set at the same distance as vehicles spawned to allow participants to see for 100% of their existence, whereas 0% visibility would set the fog line at the minimum crossing distance for a vehicle. The fog line would move between the 0% and 100% points based on the visibility percentage of the specific trial. The fog line is where nothing beyond that distance is visible to the participant.

This study's number of active lanes necessitates describing the procedure used to create gaps between vehicles. Previous laboratory research using virtual reality simulations has primarily focused on one lane of approaching vehicles from one direction (Davis et al., 2021; Davis & Barton, 2021; Morrongiello et al., 2019; Pugliese et al., 2020). For one-lane conditions, the gaps are the distance in time between the first car's rear bumper and the front bumper of the following vehicle. For multi-lane traffic gaps, 1-3 vehicles traveling in close proximity across lanes and readily distinguishable from other traffic (referred to as pods from here on) were included in the calculations rather than using individual vehicles to determine gaps. Each pod of vehicles spawned utilizing an algorithm based on the minimum gap size needed to cross between two pods of vehicles with a small amount of added variability to increase realism. Multi-lane traffic gaps are the distance in time between the rear bumper of the last car in a pod of vehicles and the front bumper of the nearest vehicle in the following pod of vehicles.

Road Crossing Performance. Road crossing performance was measured using two modified metrics used frequently in previous research: time left to spare (Morrongiello et al., 2016) and likely collisions (O'Neal et al., 2016). Time left to spare refers to the amount of time, in seconds, remaining for the approaching vehicle to intersect with the participants path at the moment the participant exits the path of the vehicle. We called this time leftover, safety time. For example, in a one-lane trial, participants' safety time would be the number of seconds before a vehicle in the first lane would reach their position after they completely crossed the first lane. Safety time could range from 0, meaning the participant had no time to spare, to the size of the gap the participant chose to cross through. Likely collisions were collected as actual collisions between the participant's avatar and a vehicle.

Procedure

The procedure for this experiment comprised several steps after informed consent and included some materials described in experiment 1. First, the demographics questionnaire was administered. Second, participants completed the Corsi Block Task. Third, participants were shown a video describing the study and their task. Finally, participants completed the pedestrian crossing task.

Analyses

Analyses proceeded in several steps. First, I screened the collected data irregular data at the participant level. Irregular data included participants that were flagged due to irregularities during data collection or data that was impacted by technical issues. Second, descriptive statistics were examined. Third, a lane (3) x speed (3) x visibility (5) repeated measures factorial ANOVA was performed to examine the impact of time pressure, task complexity, and environmentally imposed sensory constraints on the safety time. Sphericity was checked for each main effect using Maulchy's test of sphericity. Where sphericity was violated, the Greenhouse-Geisser correction was used. Interactions were excluded from analyses to stay consistent with the originally stated hypotheses, and a large number of levels in factors make interpretation difficult. Fourth, because nonverbal working memory span was measured continuously, including the Corsi accuracy measure as a between-subject measure in the factorial ANOVA would have been inappropriate. Instead, a correlation was done to determine the relationship between nonverbal working memory span and average safety time for each participant. Finally, a set of logistic regressions using a generalized linear mixed model procedure was performed to identify the relative impact of time pressure, task complexity, nonverbal working memory limit, and environmentally imposed sensory limitations on the likelihood of being struck by a vehicle.

Like study 1, regressions were performed using a generalized mixed effect model procedure to account for the repeated-measures nature of the study. Mixed models consider the correlated residuals of repeated measures designs (Galwey, 2014). A typical regression would force significance for repeated measures even if significance does not exist due to the correlated residuals of each within-subjects measure. Generalized linear mixed models were performed in two steps (Sommet & Morselli, 2017). The first step examined model tested for significant clustering effects for participant-level data. The second model includes all of the components hypothesized as predictors of injury.

Chapter 3 : Results

Experiment 1

Sex Differences and Descriptive Statistics

Sex differences in performance and failure rates were examined in a series of independent-samples t-tests and chi-square tests of independence. No significant systematic differences were found, with significance values ranging from $p = .05$ and $p = .98$. Therefore, sex was excluded in all subsequent analyses. Descriptive statistics for performance are reported in table 3.1.

Performance-Shaping Factor Impact on Performance

MOT performance was evaluated in a targets (4) x speed (3) x salience (6) repeated-measures ANOVA, see figures 3.1-3.3. Significant main effects were found for all variables. A significant main effect was found for the number of targets being tracked, F (2.58, 159.67) = 286.59, $p < .01$, partial $\eta 2$=0.82 (Maulchy's: $\chi 2$ (5) = 16.411, $p < .05$). Bonferroni follow-up tests showed a significant difference in target tracking accuracy across all conditions, with accuracy significantly decreasing as the number of targets increased. There was also a significant main effect for the speed of objects being tracked, F (2, 124) = 486.85, $p < .01$, partial $\eta 2$ = .89 (Maulchy's: $\chi 2$ (2) = 2.86, $p > .05$). Bonferroni follow-up tests showed a significant difference in target tracking accuracy across all conditions, with accuracy significantly decreasing as the speed of targets increased. Finally, there was also a significant main effect of salience, F (5, 310) = 17.80, $p < .01$, partial $\eta 2$ = .22 (Maulchy's: $\chi 2$ (14) = 22.86, $p > .05$). Bonferroni follow-up tests revealed a more complex pattern of change across the saliency conditions. Differences in accuracy were generally larger for larger changes in saliency. Still, accuracy does not seem to be significantly impacted by the saliency of the tracked objects until salience reaches 10%.

To better understand the relationship between performance and nonverbal working memory span, a correlation was performed between Corsi accuracy scores and average performance across all conditions for each participant. Corsi accuracy and average participant performance on the MOT task were moderately positively correlated, r (64) = .32, $p < .01$.

	Salience	10%	20%	40%	60%	80%	100%
Targets	**Speed**	M (SD)	M (SD)	M (SD)	M (SD)	M (SD)	M (SD)
2 Targets	1X	0.76 (0.31)	0.85 (0.25)	0.93 (0.20)	0.93 (0.20)	0.91 (0.23)	0.92 (0.18)
	2X	0.60 (0.34)	0.63 (0.31)	0.75 (0.28)	0.76 (0.31)	0.72 (0.28)	0.71 (0.32)
	3X	0.40 (0.31)	0.48 (0.33)	0.49 (0.33)	0.52 (0.31)	0.52 (0.29)	0.53 (0.37)
3 Targets	1X	0.66 (0.31)	0.73 (0.27)	0.71 (0.25)	0.75 (0.27)	0.78 (0.25)	0.77 (0.25)
	2X	0.41 (0.30)	0.50 (0.27)	0.57 (0.28)	0.52 (0.27)	0.56 (0.29)	0.61 (0.26)
	3X	0.30 (0.21)	0.35 (0.22)	0.41 (0.24)	0.37 (0.28)	0.37 (0.22)	0.40 (0.27)
4 Targets	1X	0.51 (0.27)	0.58 (0.26)	0.61 (0.26)	0.61 (0.25)	0.60 (0.26)	0.67 (0.22)
	2X	0.37 (0.18)	0.38 (0.17)	0.42 (0.22)	0.39 (0.24)	0.39 (0.21)	0.45 (0.21)
	3X	0.32 (0.19)	0.34 (0.16)	0.31 (0.17)	0.27 (0.20)	0.31 (0.18)	0.30 (0.18)
5 Targets	1X	0.48 (0.20)	0.52 (0.23)	0.51 (0.18)	0.57 (0.19)	0.53 (0.22)	0.53 (0.24)
	2X	0.35 (0.19)	0.36 (0.21)	0.37 (0.19)	0.36 (0.19)	0.39 (0.20)	0.35 (0.18)
	3X	0.24 (0.18)	0.28 (0.16)	0.28 (0.19)	0.32 (0.18)	0.29 (0.15)	0.28 (0.19)

N=63

Table 3.1. Descriptive statistics examining the average performance for each condition, study 1.

Figure 3.1. The main effect of targets on accuracy, study 1.

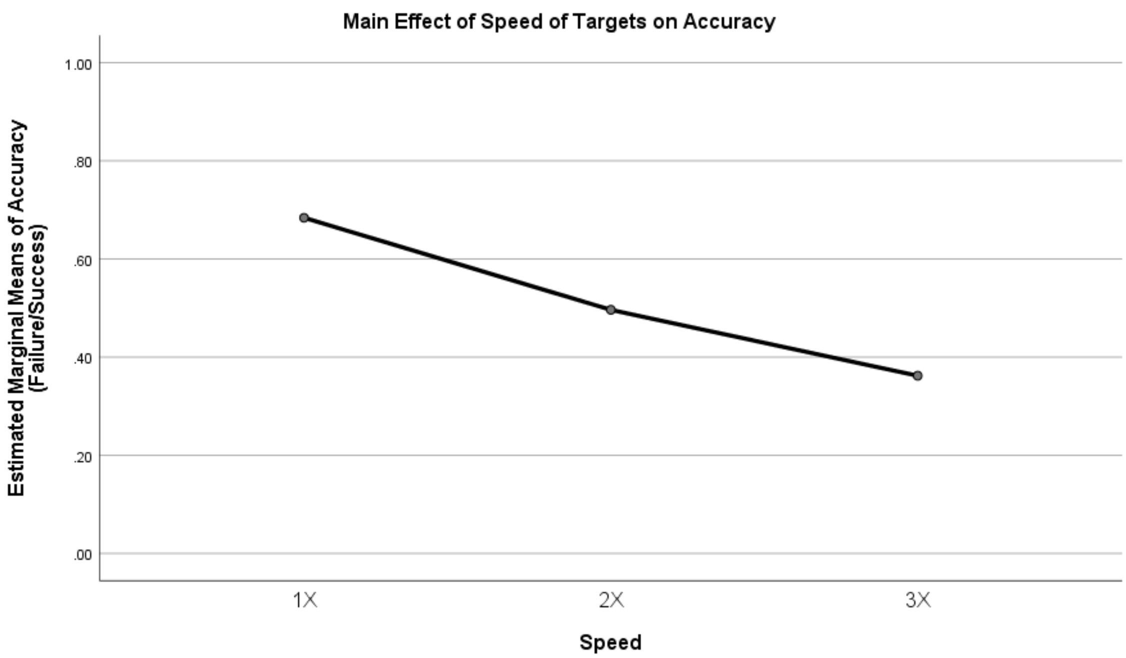

Figure 3.2. The main effect of speed on accuracy, study 1.

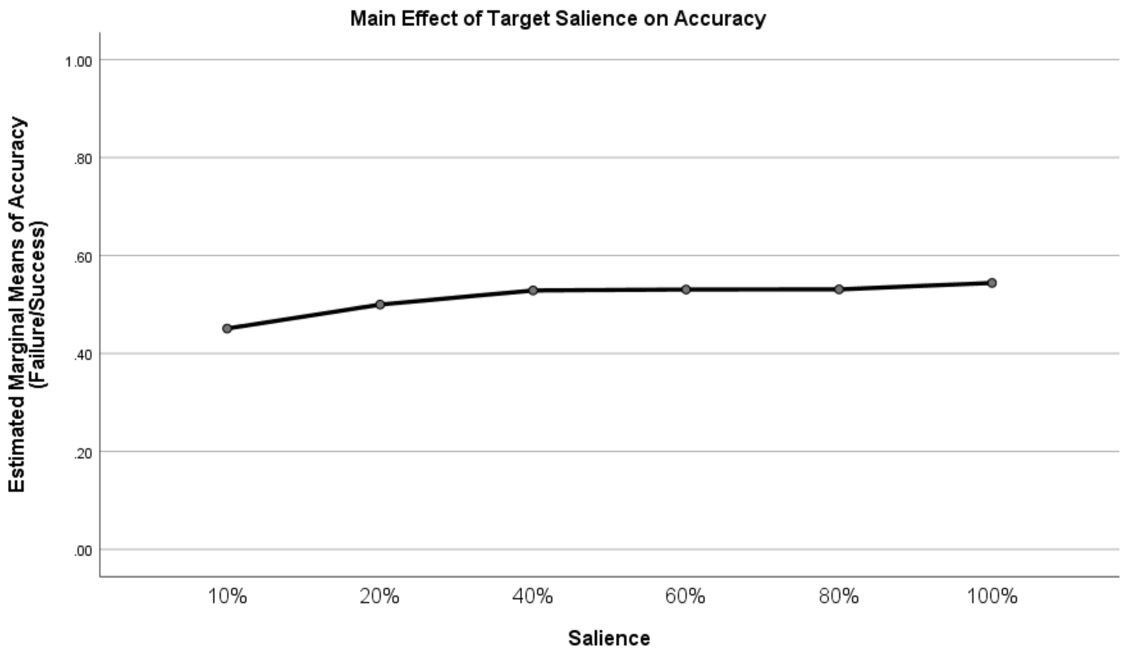

Figure 3.3. The main effect of salience on accuracy, study 1.

Performance-Shaping Factor Impact on Error Rate

Intercept-only model. Participants were added to the initial model to assess performance clustering across participants. A significant random effect was found for participants, $Z = 3.86$, $p <.01$, with an interclass correlation of $ICC = .08$. The significant results of the intercept-only model support the use of a mixed model approach with participant scores showing significant clustering.

Performance-shaping model. All predictors, number of targets, speed of targets, the salience of target, and Corsi tapping task accuracy were significantly predictive of error. The number of targets and target speed were positively predictive of error, while CBT accuracy and salience were negatively predictive of error. See table 3.2 for the odds ratios, t-tests, and confidence intervals. The final model correctly predicted 95% of the errors committed on the MOT task and 65% of successes. The final model was 90% correct on all predictions. Taken together these results mean the number of targets being tracked, the speed of targets, the salience of targets, and the participant's nonverbal memory span significantly impact performance and error rate.

Model Term	Coefficient (B)	Odds Ratio (Exp B)	Odds Ratio (95% CI)	t-value	p-value
Intercept	-4.79	0.01	0.01 - 0.03	-8.15	<.01
Targets	1.80	6.04	5.40 - 6.74	31.81	<.01
Speed	1.69	5.43	4.80 - 6.13	27.02	<.01
Salience	-0.01	0.99	0.98 - 0.99	-7.90	<.01
Corsi Accuracy	-2.84	0.06	0.01 - 0.45	-2.73	<.01

Table 3.2. Generalized linear mixed model logistic regression data for study 1.

Experiment 2

Sex Differences and Descriptive Statistics

Sex differences in performance and failure rates were examined in a series of independent-samples t-tests and chi-square tests of independence. No significant systematic differences were found, with significance values ranging from $p = .04$ and $p = .99$. Therefore, sex was excluded in all subsequent analyses. Descriptive statistics for performance are reported in table 3.3.

Performance-Shaping Factor Impact on Crossing Performance

Road crossing performance was evaluated in a lane (3) x speed (3) x visibility (5) repeated-measures ANOVA, see figures 3.4-3.6. Significant main effects were found for all variables. A significant main effect was found for the number of lanes, F (1.30, 103.58) = 22.12, $p < .01$, partial $\eta 2$ = .22 (Maulchy's: $\chi 2$ (2) = 62.15, $p < .05$). Bonferroni follow-up tests showed a significant difference in safety time across all conditions, with safety time significantly decreasing as the number of lanes increased. There was also a significant main effect for the speed of vehicles, F (1.72, 137.12) = 298.95, $p < .01$, partial $\eta 2$ = .79 (Maulchy's: $\chi 2$ (2) = 14.42, $p < .05$). Bonferroni follow-up tests showed a significant difference in safety time across all conditions, with safety time significantly decreasing as the speed of targets increased. Finally, there was also a significant main effect of visibility, *F* (3.55, 284.35) = 11.89, $p < .01$, partial $\eta 2$ = .13 (Maulchy's: $\chi 2$ (9) = 21.53, $p < .05$). Bonferroni follow-up tests revealed a less intuitive pattern of change in safety time across the visibility conditions. Safety time generally increased as visibility increased except for the 60% visibility condition (*M* = .71, *SD* = .08) which had around the same level of performance as the 20% condition (*M* = .73, *SD* = .09).

To better understand the relationship between performance and nonverbal working memory span, a correlation was performed between Corsi accuracy scores and average performance across all conditions for each participant. Corsi accuracy and average safety time on the crossing task were weakly positively correlated, *r* (79) = .22, $p < .05$.

	Visibility	20%	40%	60%	80%	100%
Lanes	**Vehicle Speed**	M (SD)	M (SD)	M (SD)	M (SD)	M (SD)
1 Lane	12mph	0.79 (0.76)	0.83 (0.93)	0.74 (1.30)	0.88 (1.25)	1.05 (0.87)
	25mph	0.64 (0.74)	0.42 (0.97)	0.57 (0.82)	0.67 (0.79)	0.60 (0.87)
	35mph	0.39 (0.85)	0.39 (0.79)	0.25 (0.88)	0.52 (0.78)	0.42 (1.05)
2 Lanes	12mph	0.98 (1.13)	1.52 (1.30)	1.34 (1.18)	1.44 (1.32)	1.66 (1.28)
	25mph	0.57 (1.02)	0.51 (1.09)	0.68 (1.05)	1.12 (1.18)	0.98 (1.13)
	35mph	0.35 (1.08)	0.66 (1.21)	0.68 (1.14)	0.63 (1.19)	0.39 (1.06)
3 Lanes	12mph	1.81 (1.78)	2.26 (1.99)	1.78 (1.71)	2.34 (2.06)	2.54 (1.99)
	25mph	0.75 (1.54)	1.08 (1.78)	0.25 (1.40)	1.23 (1.89)	0.89 (1.43)
	35mph	0.31 (1.48)	0.53 (1.65)	0.09 (1.34)	0.48 (1.60)	0.17 (1.08)

N=81

Table 3.3. Descriptive statistics examining the average safety time buffer for each condition, study 2.

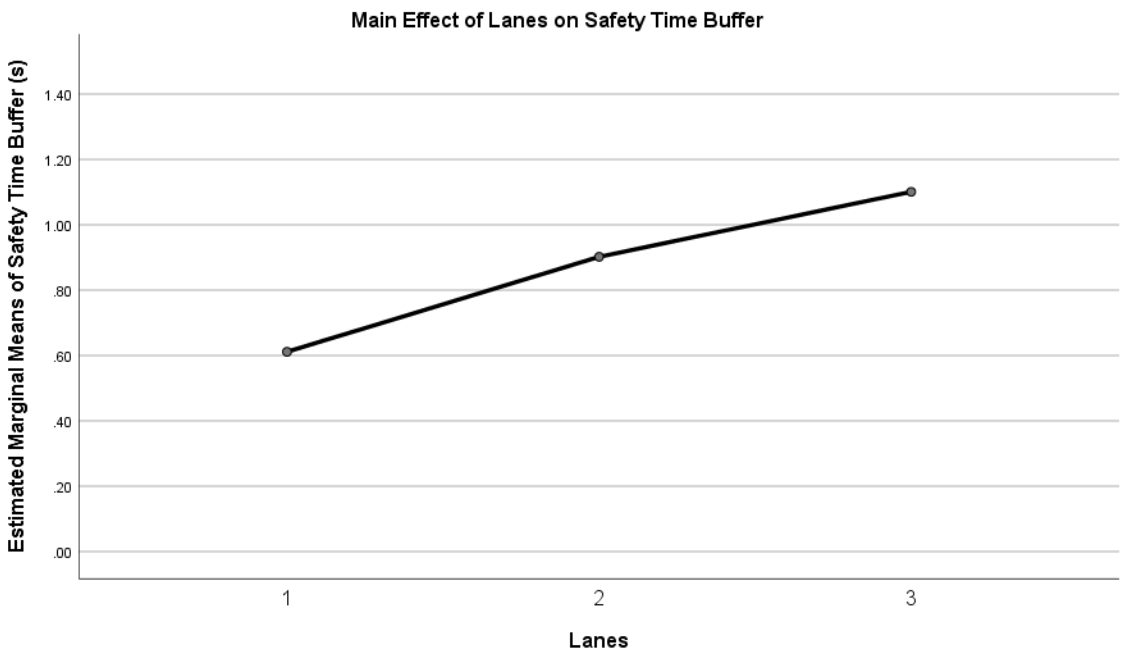

Figure 3.4 The main effect of number of lanes on safety time buffer, study 2.

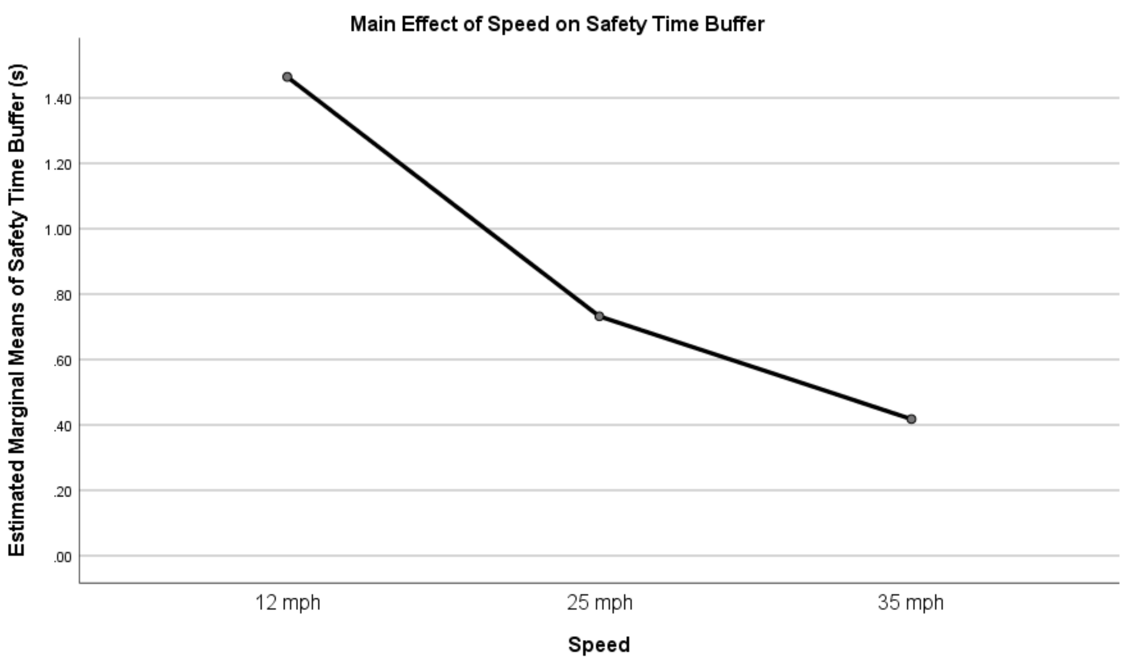

Figure 3.5 The main effect of vehicle speed on safety time buffer, study 2.

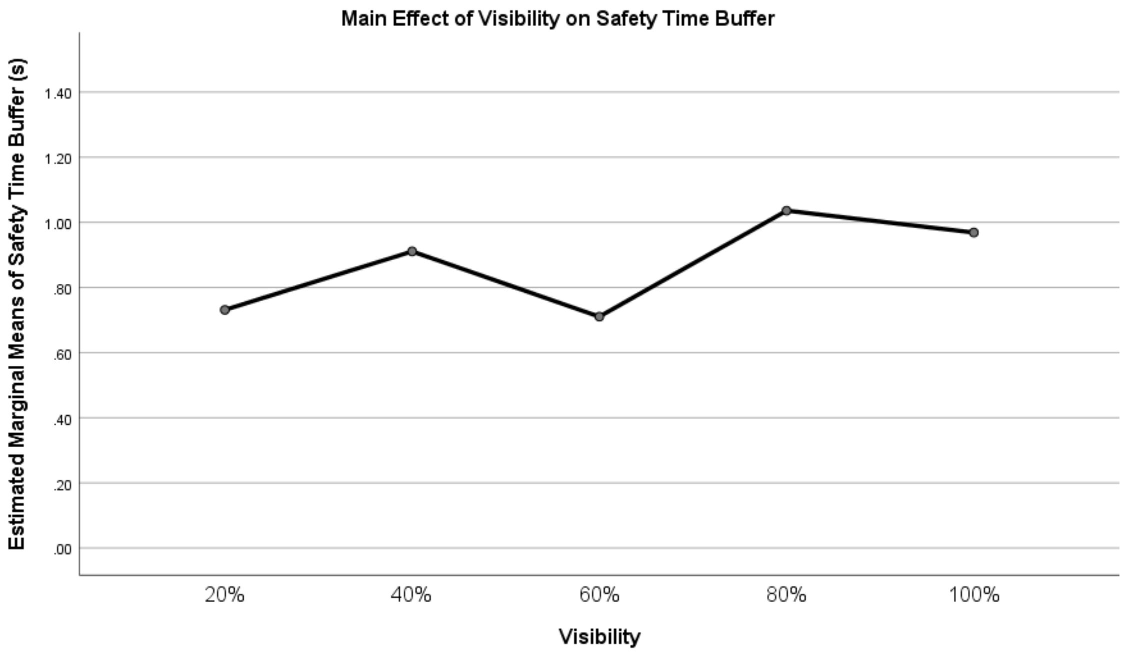

Figure 3.6 The main effect of visibility on safety time buffer, study 2.

Performance-Shaping Factor Impact on Crossing Failures

Intercept-only model. Participants were added to the initial model to assess performance clustering across participants. A significant random effect was found for participants, $Z = 5.07$, $p < .01$, with an interclass correlation of $ICC = .17$. The significant results of the intercept-only model support the use of a mixed model approach with participant scores showing significant clustering.

Performance-shaping model. All predictors, lanes, speed of vehicles, visibility of vehicles, and Corsi tapping task accuracy were significantly predictive of being struck by a vehicle while crossing a virtual road. The speed of approaching vehicles was positively predictive of error, while the number of lanes, Corsi accuracy, and opacity was negatively predictive of injury. See table 3.4 for the odds ratios, t-tests, and confidence intervals. The final model correctly predicted 72% of the success and failures. Taken together these results mean the number of vehicles, the speed of vehicles, the visibility of vehicles, and the participant's nonverbal memory span significantly impact crossing safety and injury rate.

Model Term	Coefficient (B)	Odds Ratio (Exp B)	Odds Ratio (95% CI)	t-value	p-value
Intercept	1.74	5.69	0.80 - 40.53	1.74	>.05
Lanes	-0.38	0.69	0.63 - 0.75	-8.02	<.01
Speed	0.10	1.10	1.08 - 1.12	10.41	<.01
Visibility	-0.48	0.62	0.48 - 0.80	-3.63	<.01
Corsi Accuracy	-3.47	0.03	0.02 - 0.42	-2.61	<.01

Table 3.4. Generalized linear mixed model logistic regression data for study 2.

Chapter 4 : Discussion

My goal was to better understand injury risk by integrating the concepts of PSFs and systems-level accident analysis. Specifically, I hoped to better understand and predict injury by applying PSFs to injury-relevant cross-contextual behaviors. Current injury research focuses heavily on domain-specific problems, limiting the generalizability of the research findings. For example, an unintentional injury study might concentrate on pedestrian injury, drowning, motor vehicle accidents, or falls. Research on the relative impact of PSFs, despite their broad use in human error and accident models, is disparate and not often done with human error models in mind (Whaley et al., 2016). My approach applies the cross-contextual capabilities of PSFs to study injury across domains.

The relative impact of PSFs was examined across two studies. Both studies focused on tracking multiple objects, a behavior relevant for various injury scenarios. In the first study, the impact of task complexity, time pressure, sensory limitations, and nonverbal working memory span were examined on an abstract multiple object tracking task. In the second study, the same PSFs were applied to a virtual reality crossing task where participants interacted with groups of vehicles approaching their position.

In both studies, the relative impact of PSFs followed a similar pattern of results on performance and error/injury rate, with the exception of task complexity. Task complexity (number of items being tracked/lanes of traffic) impacted performance and error/injury rate differently across the two studies. The results from both studies suggest performance and error/injury rate on a task requiring multiple object tracking is degraded by sensory limitations (reduced salience/visibility due to fog), time pressure (the speed of objects/vehicles being tracked), and individual differences in psychological ability (nonverbal working memory span). The following sections discuss the results in relation to relevant literature. Each PSF will be discussed independently in relation to performance and error/injury. Following the discussion on each PSF and results of the studies, general impact and study limitations are discussed.

Impact of Performance-Shaping Factors

Task Complexity- Number of Objects and Lanes

MOT performance and error/injury rate findings fit well with previous research regarding the abstract MOT task but not the applied pedestrian setting task. Previous research indicates degradation in performance for MOT tasks when an individual is required to track more targets (Pylyshyn & Storm, 1988; Trick et al., 2005). There is also support for a reduction in performance in applied settings, such as the tracking of multiple streams of vehicles while driving (Lochner & Trick, 2014). Similar to previous work, the abstract MOT task showed a significant decrease in performance and a larger likelihood of error when more objects were required to be tracked. However, study two's performance and error/injury results showed a contradictory relationship. In the pedestrian task, an increase in the number of lanes of traffic increased safe behavior.

One potential explanation for the contradictory outcomes between the two studies is the number of items being tracked. According to previous MOT research, humans can track up to between 4 and 8 objects, depending on the context (Meyerhoff et al., 2017; Scholl, 2019; Scholl et al., 2001). The number of objects being tracked pushed the limits of multiple object tracking for the abstract tracking task. On the other hand, the pedestrian task only reached three total lanes (assuming participants tracked each lane independently), well within the number of objects a human can track at once. There is also the possibility participants did not track lanes of traffic at all. Instead, participants may have been tracking the available gaps between each pod of vehicles, meaning participants may have only ever been tracking one object at a time. Furthermore, crossings with more lanes of traffic involved would require participant avatars to spend more time sharing the road with potentially dangerous vehicles. With the potential for less strenuous tracking than expected and the increased amount of time avatars spent in the road with vehicles, participants may have chosen to be more conservative with their 3-lane crossings than their 1-lane crossings.

Another possible explanation for the contradictory outcome of the pedestrian task is the necessarily increased distance of crossable gaps. A crossable gap for one lane of traffic only needs to account for the time a pedestrian needs to travel across one lane, about 4m. Alternatively, crossing in front of 2 or 3 lanes of traffic would require safe gaps to allow a participant to cross 8m or 12m, respectively. This increase in time needed for more lanes means vehicles are further away when participants decide to cross a street with 3-lanes of traffic than one. While the increase in the distance might intuitively lead to the assumption that crossing would be more difficult as further time-to-contact estimates are usually less accurate (Davis & Barton, 2021), the inclusion of crossable and uncrossable gaps may have reduced the impact. The increase in distance for crossings also meant that the crossable and uncrossable gaps for 3-lanes of traffic had greater absolute differences than 1-lane of traffic. The larger the number, the greater the absolute difference caused by percent changes.

Time Pressure-Speed

My findings echo findings from previous research regarding the speed of tracked objects. In a strictly MOT sense, an increase in object speed is associated with a reduced ability to track objects (Alvarez & Franconeri, 2007; Holcombe & Chen, 2012) successfully. The faster object speed potentially overwhelms an individual's processing ability to track and predict object motion. In an all-or-nothing paradigm, where missing even one tracked object results in failure of the task, poorer performance should translate directly to a higher error rate- a similar pattern to what is seen in the abstract MOT task. In a more applied sense, previous pedestrian injury literature has found a link between vehicle speed for one lane of approaching traffic and riskier crossing decisions (Davis & Barton, 2021; Morrongiello et al., 2016). An increase in vehicle speed has been associated with degradation in crossing performance and an increase in the likelihood of being struck by a vehicle (Morrongiello et al., 2016). Results from study two support the impact of speed on pedestrian safety, with performance decreasing and injury rate increasing with an increase in vehicle speed. Overall, the literature supports the degradation in tracking performance and error/injury rate when tracking faster moving objects.

Regarding vehicular speed in pedestrian environments specifically, one potential explanation for the impact of speed on safety time and injury rate is the change in judgment requirements. First, greater distances have been associated with worse time-to-contact estimates in previous pedestrian work (Davis & Barton, 2021; Pugliese et al., 2020). A faster moving vehicle, by necessity, needs to be farther away to create the same time gap as a slower moving vehicle. This increase in distance may require a greater level of processing to cross in front of.

Sensory Limitations- Salience and Visibility

The results of studies one and two show salience/visibility as an important characteristic of an individual's ability to track objects. However, in study 1, the salience of objects did not impact performance and error rate until they reached about 20% salience, while study 2 showed a systematic degradation of performance. Both sets of findings make sense in the contexts of their studies, but the results regarding the abstract MOT task are less supported by the literature. Previous research using abstract MOT tasks has not directly examined the impact of salience, but other surface features, such as shape or color, have only been found to impact MOT task performance in particular circumstances (Meyerhoff et al., 2017; Papenmeier et al., 2014). For example, the color of objects might impact performance on an MOT task when there is a color discrepancy between targets and distractors but not when all objects share the same surface features. Extending surface feature thinking to salience, a reduction in performance at any level would not have been expected. One explanation for the impact of salience found in the abstract MOT task includes a large variability of visibility levels. Salience may not impact performance and error rate until the visibility is reduced to a low enough level.

The systematic reduction in performance in the pedestrian task aligns well with previous work examining the impact of fog in the driving literature. Previous research has shown fog negatively impacts an individual's driving performance by reducing hazard avoidance efficacy, less vehicle control, more steering variability, and higher speeds (Li et al., 2015; Mueller & Trick, 2012). On the other hand, one study examining the impact of fog on pedestrian behavior found no impact on choosing safe gaps and time-to-contact judgments (Davis & Barton, 2021). The operationalization of how the fog was implemented across the different studies may have impacted the results. In Davis & Barton (2021), the fog line was set at a specific distance regardless of vehicle characteristics, and the fog was either present or not. Instead, the pedestrian task presented here changed the fog's characteristics to provide the same visibility for each stream of traffic—consistent visibility rather than consistent fog.

One potential reason for the pattern of results seen in the abstract MOT task is how the nature of the task interacts with our ability to track objects. In terms of behavior at the macrocognitive level, salience is more strongly linked to object detection than tracking objects (Levi, 2008; Whaley et al., 2016). Once an object is detected, tracking relies more on temporospatial processing than feature processing (Papenmeier et al., 2014). Still, with low enough opacity, objects begin to blend with the background characteristics, and the background becomes another potential distractor (Cuthill et al., 2019). The background becoming another distractor might explain why performance did not seem to degrade in the abstract task until opacity reached about 20%. Before opacity reached 20%, the targets and distractors were salient enough to be easily differentiated from the background.

Similar reasoning likely impacts the pattern of results regarding visibility in the pedestrian task as the abstract task. Like the abstract task, at the macrocognitive level, the pedestrian task focused on tracking rather than detection, making visibility a bit less impactful. Still, the presence of fog potentially softens cues used to make crossing judgments and gives participants less time to process information regarding approaching vehicles. Having less time to process the approaching vehicles may have led to riskier judgments (Pugliese et al., 2020). The pedestrian and abstract task differences potentially stemmed from the reduced time participants had with the tracked objects. In the abstract task, participants only briefly lost sight of objects when other objects occluded them. In contrast, the pedestrian task objects were only visible after they emerged from the fog.

Individual Differences in Ability- Nonverbal Working Memory Span

The results from study one and two agree with previous findings that individuals with a lower nonverbal working memory span perform worse on MOT tasks. In terms of the abstract MOT task, the actual task has been likened to a test of visual attention (Meyerhoff et al., 2017). If construct reliability is assumed, a relationship between two measures of similar constructs should be correlated with one another. Furthermore, previous research has found evidence of a shared mechanism for MOT and nonverbal memory span (Chesney & Haladjian, 2011). In terms of the pedestrian task, previous research has also found links between nonverbal working memory, visual search in a pedestrian setting, safe gap selection, and time-to-contact estimates (Davis & Barton, 2021; Kovesdi & Barton, 2013). In dynamic, complex environments such as a pedestrian setting, the ability to filter through unimportant information and focus on relevant crossing information would be expected to align with safer behavior.

General Discussion

Human Error

The study of human error is a largely inductive endeavor. Generally, human error is examined in retrospect, and the antecedents leading to error are divined by analysts (Salmon et al., 2011). If an analyst is predisposed to believing humans are the problem, they might overlook the contribution of a technological system. Natural human biases further complicate the retrospective and inductive nature of looking for antecedents carry with them when drawing conclusions (Hollnagel, 2007; Sharit, 2012). For example, the availability and confirmation bias both make retrospective accident analysis a difficult practice.

This is not to say human error models cannot be predictive, but many predictive models also work inductively. Starting with the potential outcomes, the analyst attempts to determine the possible ways in which a process can fail, then attempts to determine the likelihood and methods for failure (Stanton et al., 2013). Even in predictive models, the inductive nature makes potential biases a serious problem in determining what impacts potential error in a system. In this case, the biases are likely built into the predictive models when initially designed.

A large body of research examining human performance has been borrowed from human error research. However, research on human performance is broad and can be difficult to synthesize succinctly (Whaley et al., 2016). Still, despite the inductive nature of the study of error, some empirical deductive work does exist. The broad and disparate nature of research on human performance partly explains the large variety of PSFs found across human error models (Groth & Mosleh, 2012). Furthermore, the relative impact of PSFs on performance is often estimated in models without the benefit of empirical support (Kim et al., 2015). For example, a commonly discussed Human Reliability Analysis method, SPAR-H, multiplies the likelihood of a human error by 10X when there is barely enough time to complete a task (Kim et al., 2018). The relative impact of time pressure may be as high as

10x, but there is no clear empirical line drawn between the likelihood of failure or even how time pressure might interact with other PSFs to impact error.

Taken together, study one and study two are a direct attempt to empirically examine the impact of PSFs on the likelihood of error at a high enough level to be useful for predicting various contexts. By examining an abstract judgment task and then applying the same PSFs to an applied setting, we can determine if examining PSFs at the macrocognitive level is appropriate to cross contexts but still successfully quantify and predict errors (Whaley et al., 2016). If the results across both activities mirror one another, we may have a new unifying method for examining error and injury.

Furthermore, we can determine how closely performance and error overlap by examining both errors and performance accuracy. Research examining error often assumes a drop in performance predicts error. The assumption that a reduction in performance is the same as predicting error makes sense but may not always be the case. If a system is resilient enough, poor performance may not lead to an attribution of error, and poor performance may not predict error (Sheridan, 2008). Poor performance probably does predict higher error rates in most things, but the relationship between performance and error has not been thoroughly examined.

Injury Prevention and Etiology

Another area that benefits from this research lie in injury etiology and prevention. Injury is still one of the most expensive and common reasons for death in the United States (National Center for Injury Prevention and Control, 2020). To have an accurate and reliable way to predict when an injury might occur, would be priceless. Especially since most unintentional injuries are thought to be preventable (L. Peterson et al., 1987). The following section discusses how my dissertation impacts injury prevention and etiology.

Injury research does a respectable job of predicting and preventing injury in specific injury domains. Sets of predictive factors have been identified for pedestrian injury (Barton, Ulrich, & Lyday, 2012), drowning (Shen et al., 2016), playground falls (Schwebel, 2006), and even poisoning (Brayden et al., 1993). Identifying risk factors for specific injuries is important and provides injury prevention efforts with specific targets. However, the modes and context of injury are potentially limitless. How can we, as safety researchers, hope to prevent unknown types of injuries in unknown contexts if we continue to study injury by domain? Rather than examining the behavioral antecedents preceding injury, we should be examining the antecedents to the system failures which lead to injury.

The work here examines unintentional injury resulting from a system failure due to error. If an unintentional injury happens unintentionally, by error, then error prediction might be a good place to target our research. By taking a step back from the specific injury domain, we can determine a general set of factors at a high enough level to permeate various injury types but low enough to help predict and prevent injury by examining how PSFs impact error rate in cross-contextual behaviors, such as in making judgments, decisions, or perceiving a problem, we essentially identify what PSFs have the potential to cause injury. The beauty of this method is researchers can apply the same thinking to any number of situations. By looking at the impact of a PS*F* like task complexity on perceptual judgments, researchers can predict and reduce potential injuries in any task where a failure in a perceptual judgment will result in an injury, such as: crossing a street, vehicle collisions, nuclear power operation, manufacturing-line injuries, some types of construction injuries, and countless other possibilities.

The linking of error to real-world cognitive functions can improve safety as early as the initial design stage of products and spaces. We can build more resilient, safe systems if we know what factors are likely to lead to errors and subsequent injury. For example, if time pressure is identified as a major contributor to object tracking failures, a road designer can design safeguards for traffic signals at a potentially dangerous intersection. By identifying and researching these factors leading to injury, we are essentially adding more protective factors, layers of Swiss cheese, to potentially dangerous systems.

Another benefit of predicting failure by cognitive function rather than domain is we can begin to unravel what transforms a near-miss into an actual injury. A risk behavior might lead to injury the first time the behavior is performed, or it might never lead to an actual injury (L. Peterson et al., 1987). By examining the PSFs associated with context and human fallibility, we can begin to unravel at what level a system of PSFs needs to be to become an injury. Rather than identifying age or experience alone to prevent future injuries, we can determine the specific sets of PSFs which lead to a failure in action and build more resilient methods for preventing those near misses from becoming full-blown injuries. For example, perhaps a skiing injury only occurs when time pressure, task complexity, and training interact. Furthermore, perhaps a risk behavior will only be a near miss if the impact of the PSFs stay below a certain threshold. Understanding the relationship between the system and behavior is paramount to understanding when an injury will occur.

Limitations

Several limitations are worth mentioning regarding the samples collected for the two studies and the experimental controls of the pedestrian task. First, the samples used in these studies consisted entirely of an undergraduate population at an inland northwest university. The samples had little diversity, potentially limiting the generalizability of both studies. Most participants were mostly female, white students between 18 and 25. The impact of the sample composition is currently unknown, but results would likely vary across development (Trick & Enns, 1998). Future research might aim for a more diverse sample to ensure that results represent the population. Second, there was a trade-off in experimental and mundane realism for the pedestrian task. The high level of control and difficult nature of the task was important for three reasons: 1) error and injury have a low base rate, so the task needed to be more difficult than normal, 2) people are generally great at crossing roads safely, 3) the experimental control was necessary to draw more solid conclusions. Despite the mentioned reasons for the task having less external validity, future studies might examine the impact of each PS*F* in less controlled settings.

Other limitations worth mentioning are the way participants crossed the street in the pedestrian task and the overall impact of COVID-19. In the pedestrian study, participants were required to choose crossing opportunities based on the set walking speed of an avatar. The use of the avatar may have impacted participant performance in two ways. 1) The use of an avatar may have impacted the overall workload of the task as participants were required to keep the avatar's movement speed on their mind while making crossing judgements, 2) The set walking speed of the avatar may not have matched the participant's mental model of their movement speed. Practice trials were used to try and minimize the impact of the crossing avatar. Finally, data for both studies was collected during the COVID-19 pandemic. Besides the extra procedures implemented in the lab, such as social distancing, mask-wearing, and increased sanitation procedures, the impact of the pandemic on cognitive, perceptual, and psychological ability is unknown.

Chapter 5 : Conclusion and Future Directions

The goal was to explore a novel method for predicting unintentional injury using concepts from the human error literature. Across two studies, I examined the relative impact of PSFs on the performance of an MOT task on performance and error/injury rate. In both studies, time pressure, task complexity, sensory limitations, and working memory capacity were manipulated as the main PSFs but applied in different contexts. In the first study, the PSFs were applied to an abstract MOT task. In the second study, the PSFs were applied to a pedestrian scenario where participants were required to track multiple lanes of traffic and make crossing decisions. Both studies showed similar results and provided a proof of concept for an early examination of error and injury together.

My dissertation sets the groundwork for a novel line of work examining how to better predict unintentional injury and error in general. By separating research from individual injury domains and focusing on cross-contextual behavioral processes, we can better predict and prevent future injuries from falling into specific categories. Furthermore, we can predict and prevent various injury types within one study as many domains of injury share similar cognitive processes. The methods discussed here make way for future predictive studies related to sensemaking, problem detection, decision making, communication, and action. Each category can be explored for the specific factors that lead to error and, therefore, injury. Beyond laboratory settings, the outlined work also provides new avenues for injury prevention agnostic of injury mode, a method for examining the design of resilient systems, and ensuring safe products.

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Appendix A: IRB Approval for Study 1

University of Idaho
Office of Research Assurances
Institutional Review Board
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Phone: 208-885-6162
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July 17, 2020

To: Benjamin K Barton

Cc: Brian Pugliese

From: University of Idaho Institutional Review Board

Approval Date: July 17, 2020

Title: Predicting Error in a Macocognitive Task using Performance-Shaping Factors

Protocol: 20-121, Reference: 010070

Exempt under Categories 2 and 3 at 45 CFR 46.104(d)(2) and (3).

On behalf of the Institutional Review Board at the University of Idaho, I am pleased to inform you that the protocol for this research project has been certified as exempt under the category listed above.

This certification is valid only for the study protocol as it was submitted. Studies certified as Exempt are not subject to continuing review and this certification does not expire. However, if changes are made to the study protocol, you must submit the changes through VERAS for review before implementing the changes. Amendments may include but are not limited to, changes in study population, study personnel, study instruments, consent documents, recruitment materials, sites of research, etc.

As Principal Investigator, you are responsible for ensuring compliance with all applicable FERPA regulations, University of Idaho policies, state and federal regulations. Every effort should be made to ensure that the project is conducted in a manner consistent with the three fundamental principles identified in the Belmont Report: respect for persons; beneficence; and justice. The Principal Investigator is responsible for ensuring that all study personnel have completed the online human subjects training requirement. Please complete the *Continuing Review and Closure Form* in VERAS when the project is completed.

You are required to notify the IRB in a timely manner if any unanticipated or adverse events occur during the study, if you experience an increased risk to the participants, or if you have participants withdraw or register complaints about the study.

IRB Exempt Category (Categories) for this submission:
Category 2: Research that only includes interactions involving educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures, or observation of public behavior (including visual or auditory recording) if at least one of the following criteria is met: i. The information obtained is recorded by the investigator in such a manner that the identity of the human subjects cannot

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readily be ascertained, directly or through identifiers linked to the subjects; ii. Any disclosure of the human subjects' responses outside the research would not reasonably place the subjects at risk of criminal or civil liability or be damaging to the subjects' financial standing, employability, educational advancement, or reputation; or iii. The information obtained is recorded by the investigator in such a manner that the identity of the human subjects can readily be ascertained, directly or through identifiers linked to the subjects, and an IRB conducts a limited IRB review to make the determination required by .111(a)(7).

Category 3: i. Research involving benign behavioral interventions in conjunction with the collection of information from an adult subject through verbal or written responses (including data entry) or audiovisual recording if the subject prospectively agrees to the intervention and information collection and at least one of the following criteria is met: A. The information obtained is recorded by the investigator in such a manner that the identity of the human subjects cannot readily be ascertained, directly or through identifiers linked to the subjects; B. Any disclosure of the human subjects' responses outside the research would not reasonably place the subjects at risk of criminal or civil liability or be damaging to the subjects' financial standing, employability, educational advancement, or reputation; or C. The information obtained is recorded by the investigator in such a manner that the identity of the human subjects can readily be ascertained, directly or through identifiers linked to the subjects, and an IRB conducts a limited IRB review to make the determination required by .111(a)(7). ii. For the purpose of this provision, benign behavioral interventions are brief in duration, harmless, painless, not physically invasive, not likely to have a significant adverse lasting impact on the subjects, and the investigator has no reason to think the subjects will find the interventions offensive or embarrassing. Provided all such criteria are met, examples of such benign behavioral interventions would include having the subjects play an online game, having them solve puzzles under various noise conditions, or having them decide how to allocate a nominal amount of received cash between themselves and someone else. iii. If the research involves deceiving the subjects regarding the nature or purposes of the research, this exemption is not applicable unless the subject authorizes the deception through a prospective agreement to participate in research in circumstances in which the subject is informed that he or she will be unaware of or misled regarding the nature or purposes of the research.

Appendix B: IRB Approval for Study 2

University of Idaho
Office of Research Assurances
Institutional Review Board
875 Perimeter Drive, MS 3010
Moscow, ID 83844-3010
Phone: 208-885-6162
Fax: 208-885-6014
Email: irb@uidaho.edu

July 17, 2020

To: Benjamin K Barton

Cc: Brian Pugliese

From: University of Idaho Institutional Review Board

Approval Date: July 17, 2020

Title: Predicting Pedestrian Injury by Predicting Error

Protocol: 20-122, Reference: 010072

Exempt under Categories 2 and 3at 45 CFR 46.104(d)(2) and (3).

On behalf of the Institutional Review Board at the University of Idaho, I am pleased to inform you that the protocol for this research project has been certified as exempt under the category listed above.

This certification is valid only for the study protocol as it was submitted. Studies certified as Exempt are not subject to continuing review and this certification does not expire. However, if changes are made to the study protocol, you must submit the changes through VERAS for review before implementing the changes. Amendments may include but are not limited to, changes in study population, study personnel, study instruments, consent documents, recruitment materials, sites of research, etc.

As Principal Investigator, you are responsible for ensuring compliance with all applicable FERPA regulations, University of Idaho policies, state and federal regulations. Every effort should be made to ensure that the project is conducted in a manner consistent with the three fundamental principles identified in the Belmont Report: respect for persons; beneficence; and justice. The Principal Investigator is responsible for ensuring that all study personnel have completed the online human subjects training requirement. Please complete the *Continuing Review and Closure Form* in VERAS when the project is completed.

You are required to notify the IRB in a timely manner if any unanticipated or adverse events occur during the study, if you experience an increased risk to the participants, or if you have participants withdraw or register complaints about the study.

IRB Exempt Category (Categories) for this submission:
Category 2: Research that only includes interactions involving educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures, or observation of public behavior (including visual or auditory recording) if at least one of the following criteria is met: i. The information obtained is recorded by the investigator in such a manner that the identity of the human subjects cannot

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readily be ascertained, directly or through identifiers linked to the subjects; ii. Any disclosure of the human subjects' responses outside the research would not reasonably place the subjects at risk of criminal or civil liability or be damaging to the subjects' financial standing, employability, educational advancement, or reputation; or iii. The information obtained is recorded by the investigator in such a manner that the identity of the human subjects can readily be ascertained, directly or through identifiers linked to the subjects, and an IRB conducts a limited IRB review to make the determination required by .111(a)(7).

Category 3: i. Research involving benign behavioral interventions in conjunction with the collection of information from an adult subject through verbal or written responses (including data entry) or audiovisual recording if the subject prospectively agrees to the intervention and information collection and at least one of the following criteria is met: A. The information obtained is recorded by the investigator in such a manner that the identity of the human subjects cannot readily be ascertained, directly or through identifiers linked to the subjects; B. Any disclosure of the human subjects' responses outside the research would not reasonably place the subjects at risk of criminal or civil liability or be damaging to the subjects' financial standing, employability, educational advancement, or reputation; or C. The information obtained is recorded by the investigator in such a manner that the identity of the human subjects can readily be ascertained, directly or through identifiers linked to the subjects, and an IRB conducts a limited IRB review to make the determination required by .111(a)(7). ii. For the purpose of this provision, benign behavioral interventions are brief in duration, harmless, painless, not physically invasive, not likely to have a significant adverse lasting impact on the subjects, and the investigator has no reason to think the subjects will find the interventions offensive or embarrassing. Provided all such criteria are met, examples of such benign behavioral interventions would include having the subjects play an online game, having them solve puzzles under various noise conditions, or having them decide how to allocate a nominal amount of received cash between themselves and someone else. iii. If the research involves deceiving the subjects regarding the nature or purposes of the research, this exemption is not applicable unless the subject authorizes the deception through a prospective agreement to participate in research in circumstances in which the subject is informed that he or she will be unaware of or misled regarding the nature or purposes of the research.