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### OPTIMIZING STADIUM EVACUATION BY INTEGRATING

## GEO-COMPUTATION AND AFFORDANCE THEORY

by

Joslyn Jane Zale

A Dissertation Submitted to the Graduate School and the Department of Geography and Geology at The University of Southern Mississippi in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy

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May 2017

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#### ABSTRACT

# <span id="page-3-0"></span>OPTIMIZING STADIUM EVACUATION BY INTEGRATING GEO-COMPUTATION AND AFFORDANCE THEORY

by Joslyn Jane Zale

#### May 2017

The purpose of this project was to optimize football stadium evacuation time by integrating geo-computation with affordance theory from perceptual psychology to account for evacuee characteristics: age, gender, physical fitness, alcohol consumption, and prior experience attending football games at The University of Southern Mississippi (USM), evacuating from large, outdoor public places, and with hazard events.

According to the Uniting and Strengthening America by Providing Appropriate Tools Required to Intercept and Obstruct Terrorism (USA PATRIOT) Act, football stadiums are part of the country's critical infrastructure warranting special government protection. Evacuation modeling was identified as an important component of game day emergency preparation. Research shows that: (1) the age, gender, and physical fitness of an individual impact his/her locomotion speed; (2) evacuation route choice is influenced by the perception of its safety and effectiveness; and (3) prior evacuation experience affects evacuation decision-making processes. By including these factors, this research, conducted at USM's M.M. Roberts Stadium, represents the reality of evacuee movement and behaviors that influence stadium evacuation time.

A questionnaire-based survey was administered to game attendees prior to a USM home game to gather evacuee attribute data that influenced locomotion speed. This data, plus secondary spatial data, were used in an agent-based model to model individual

evacuee movement. The time required for all evacuees to exit the stadium and campus was 165.16 minutes. This time was significantly shorter than evacuation times from the same location using non-location-specific evacuee locomotion speeds, suggesting that use of local data is vital to accurately depicting evacuation time. The findings also indicated that age and gender were the two main factors that impacted locomotion speeds.

The main contributions of this study were: (1) optimizing evacuation time by using location-specific locomotion speeds and (2) providing insights into how evacuees' physical and mental health influence their evacuation decision-making processes. The U.S. government and sports management industry could use these findings to increase game day safety and security. Due to the spatiotemporal nature of evacuation modeling and perceptions of evacuees that impact evacuation time, this research contributed to the fields of geography, computer science, sport management, psychology, and emergency management.

#### ACKNOWLEDGMENTS

<span id="page-5-0"></span>Many thanks to my advisor, Dr. Bandana Kar, and my dissertation committee, Drs. David Cochran, George Raber, Andy Reese, and Stacey A. Hall, for advice and assistance as I completed this research.

Thanks also to Dr. J.T. Johnson, former Director of the Center for Research Support at USM, for assistance with questionnaire development and statistical analysis, Ms. Jessica Moehl of the Geographic Information Science and Technology Research Area in the Computing and Computational Sciences Directorate at Oak Ridge National Laboratory for survey administration advice, and Dr. Lou Marciani, Director of the National Center for Spectator Sport Safety and Security (NCS4), for help with survey logistics. I appreciate the assistance of Ms. Lucy Bowens (USM's Director of Parking Management) and Ms. Jennifer Hatten (USM's Parking Management Administration and Systems Specialist), who explained where on campus football game attendees park and provided the number of spaces per parking lot.

Gratitude to Mr. Louis Schijve, President and CEO, Mr. Fred Jansma, Chief Technology Officer, and Mr. Charles Lester, Simulation Applications Consultant, all with INCONTROL Simulation Solutions, for sharing their simulation knowledge and providing a computer, Pedestrian Dynamics developer's license, and in-kind support. I could not have completed this research without their assistance, and am extremely grateful for the many hours Mr. Lester devoted to helping me learn the Pedestrian Dynamics software, debugging the model, and ensuring the performance of the model met the needs of this research.

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Finally, I appreciate the many people who made questionnaire administration possible. Mr. Kent Hegenauer (USM's Deputy Director of Athletics) gave me permission to administer the questionnaire prior to the football game on October 3, 2015, and Nicole Callais, Xiaohui Liu, Haipeng Tang, Cody Knuth, James Thompson, Shaquira Bradfield, Glenn Greer, Brooklyn Mills, Morgan Milburn, Haden Anderson, Lauren Bartholomay, and Rachel Jacobson administered the questionnaire.

This research was funded by the 2014 and 2015 Arthell Kelley Research Initiative for Graduate Students in Geography from the Department of Geography and Geology at The University of Southern Mississippi.

My doctoral studies were funded by the Department of Homeland Security Grant Award HSHQDC-12-C-00057 and the National Science Foundation Grant Award CMMI-1335187. The views and conclusions in this document are mine and should not be interpreted as representing the policies or opinions of the funding agencies.

## DEDICATION

<span id="page-7-0"></span>I wish to thank my parents, Ray and Lynn Zale, my sister, Lauren Zale, and my extended family for their support throughout my doctoral studies.



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#### CHAPTER I – PROBLEM STATEMENT

<span id="page-16-0"></span>The purpose of this research was to optimize evacuation time from the M.M. Roberts Stadium at The University of Southern Mississippi (USM) in Hattiesburg, MS, and its surroundings by integrating pedestrian and vehicular evacuation models. The two main objectives of this research were to (1) examine the role of affordance theory (i.e., evacuees' perception of a hazard, the need to evacuate, evacuation route choice, and experience evacuating from large, outdoor public places) in optimizing stadium evacuation time and (2) optimize evacuation time by implementing agent-based modeling in conjunction with affordance theory and physical attributes of evacuees (i.e., age, gender, physical fitness level as estimated by body mass index (BMI), and blood alcohol concentration (BAC)). This chapter introduces the research issue, the project objectives, and expected outcomes of the research.

#### Research Issue Introduction

<span id="page-16-1"></span>The American professional sports industry is a billion dollar industry that was worth about \$435 billion in 2012, an increase of about \$15 billion from 2009 (Sports 2013; Zale and Kar 2012). Football, the most-watched and lucrative professional sport in the U.S., generated \$12 billion during the 2014 season and had an average fan attendance of 68,274 at regular season games in 2015 (Wattles 2015; NFL 2016). According to the National Collegiate Athletic Association (NCAA), total fan attendance at college football games reached a record high of about 50 million in 2013 (NCAA n.d.). Because watching football is a popular and revenue-generating past-time, the U.S. government created legislation and programs to protect football stadiums, audiences, and their economic value. For instance, the USA PATRIOT Act requires protection of stadiums (considered

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part of the nation's critical infrastructure) because they represent American culture and promote mass gatherings (USA PATRIOT ACT 2001). The *Congressional Research Service (CRS) Report* of 2004 also stated that major athletic competitions are high profile events that require special protection (Moteff and Parfomak 2004). Therefore, industry professionals and researchers, such as the International Association of Venue Managers (IAVM) - an organization for facility managers, and the National Center for Spectator Sport Safety and Security (NCS4) at USM have created best practice guidelines addressing safety, security, emergency preparedness, emergency response training, and evacuation planning for sporting events (Hall et al. 2010; Hall 2013; McGee et al. 2013).

Large numbers of people gather in a relatively small area in football stadiums. Thus, staging a full-scale evacuation drill in a 30,000-seat stadium is time- and costprohibitive, and accurately replicating the range of human reactions to a real emergency during practice is difficult (Johnson 2006; Baker et al. 2007). An alternative solution is to implement computer-simulated evacuation models, which reduce time and cost of emergency planning and preparation for hazard events (e.g., severe thunderstorm, bomb threat) (Johnson 2006; Baker et al. 2007). Computer-based stadium-specific training, modeling, and simulation have been identified as part of evacuation planning and stadium security management standards that these types of venues should address to promote safety and security (Gips 2003; Pantera et al. 2003; Hall 2008; Phillips et al. 2006; Hall et al. 2008).

An individual evacuee's locomotion speed (i.e., exiting an evacuation zone on foot) and how it is affected by herding behavior, panic, and evacuation route affordance (i.e., evacuees' perception of available evacuation routes) are used in modeling

evacuation from warehouses, museums, and rooms (Yang et al. 2002; Parisi and Dorso 2005; Was 2005; Varas et al. 2007; Joo et al. 2013; Pluchino et al. 2013). In contrast, vehicular evacuation models use driving speed and drivers' decision-making processes to evacuate from larger areas, such as a 10-mile radius surrounding a nuclear power plant (Stern and Sinuany-Stern 1989; Cova and Johnson 2003; Pal et al. 2003; Chen 2008).

Although evacuation models use numerous input parameters, they rarely include evacuees' physical and psychological characteristics, which influence a timely and orderly evacuation (Gibson 1966, 1979; Hinmann et al. 1988; Spyropoulos et al. 1997; Bohannon 1997; Samson et al. 2001; Lindell et al. 2005). Joo et al. (2013) is one such study, in which pedestrian evacuation was determined based on evacuees' evacuation route affordance. Likewise, very few studies have combined pedestrian and vehicular evacuation for a venue of mass gathering (e.g., a football stadium - Zale and Kar (2012)). This research attempted to combine pedestrian and vehicular movement within and surrounding a football stadium to optimize evacuation time based on evacuees' psychological and physical attributes.

#### Project Objectives

<span id="page-18-0"></span>The goal of this research was to optimize evacuation time from M.M. Roberts Stadium and the surrounding campus (in Hattiesburg, MS) by integrating vehicular and pedestrian evacuation models. Previous research shows that: (1) age, gender, and BMI of an individual affect his/her locomotion speed, (2) prior evacuation experience affects the decision to evacuate and evacuation time, and (3) the perception of safe and effective evacuation routes affects evacuation time (Gibson 1966, 1979; Hinmann et al. 1988; Spyropoulos et al. 1997; Bohannon 1997; Samson et al. 2001; Lindell et al. 2005; Joo et

al. 2013). Although the individual impacts of locomotion speed, prior evacuation experience evacuating, and perception of safety and evacuation route effectiveness on evacuation have been examined, the collective effect of these variables has rarely been investigated (Lindell et al. 2005; Joo et al. 2013).

In this study, the evacuee characteristics of age, gender, BMI, BAC, and affordance attributes (i.e., prior experience attending USM football games, evacuating from large and outdoor public places, and with hazard events) were used in an agentbased model to simulate evacuee movement within the stadium, along with network analysis to determine the time required to evacuate the stadium and its surroundings (Figure 1). The following objectives and research questions were examined to accomplish the research goal.

- 1. Objective 1: Determine the impact of evacuees' attributes on evacuation time.
	- To what extent do evacuees' physical attributes (i.e., age, gender, BMI, and BAC) and affordance attributes (identified above) influence their evacuation decision and time to evacuate from the M.M. Roberts Stadium?
- 2. Objective 2: Optimize evacuation time.
	- How does evacuation time vary based on the aforementioned evacuee attributes?
	- How do the results of this research compare with other stadium evacuation models (e.g., Zale 2010; Pedestrian Dynamics 2017)?



#### <span id="page-20-1"></span>*Figure 1.* Evacuation model diagram.

Provides a general overview of the evacuation process. Determination of the number and locations of evacuees are shown in gold. The evacuation steps for uninjured and injured evacuees are shown in blue and red, respectively. Determination of evacuation routes, calculation of evacuation time, and model assessment are shown in green.

#### Outcomes

<span id="page-20-0"></span>An important outcome of this research is gaining insight about how evacuees' physical and psychological attributes influence the total time required to exit a stadium

and its immediate surrounding area. Due to the inclusion of these attributes, the methodology presented in this study depicts a more realistic depiction of evacuation time to aid in resource protection and evacuation preparation and response. Other outcomes include: (1) determining both pedestrian and vehicular evacuation times, (2) the combined impact of pedestrian and vehicular evacuation on total evacuation time, and (3) a model/methodology that can be replicated in other stadiums/mass gathering venues.

#### CHAPTER II - BACKGROUND

<span id="page-22-0"></span>First, this chapter provides an overview of evacuation modeling. Next, it explains cellular automata and agent-based modeling methodologies that have extensively been used in evacuation modeling to increase its accuracy. An overview of affordance theory from perceptual psychology and a discussion of modeling the effects of panic and BAC on evacuation is also presented. Finally, a summary of evacuation modeling research issues is provided, justifying the need for this project.

#### Evacuation Modeling Overview

<span id="page-22-1"></span>Evacuation modeling started in the 1980s in response to the Three Mile Island (1979) and Chernobyl (1986) incidents (Urbanik et al. 1980; Sheffi et al. 1982; Stern and Sinuany-Stern 1993; Cova and Church 1997). With the increase in the number of recorded natural hazards by almost three times between 1970 and 2000 (UN 2004), the focus of evacuation modeling shifted from human-made hazards to natural hazards, especially tropical storms (Hobeika and Jamei 1985; Pal et al. 2003; Chen 2008), floods (Pal et al. 2003), and wildfires (Cova and Johnson 2002; Church and Sexton 2002; Cova at al. 2005). After the World Trade Center terrorist attacks on 9/11/2001, evacuation modeling due to anthropogenic hazards was revisited (Pal et al. 2003; Georgiadou et al. 2007). In addition to the type of hazard, evacuation models can be categorized by methodology into flow-based, agent-based, or cellular-automata-based models (Table 1).

#### Table 1

#### <span id="page-23-0"></span>*Evacuation Modeling Methods*



Flow-based evacuation models depict evacuees as a continuous stream or flow that moves from an origin along specific evacuation routes to potential destinations (De Silva and Eglese 2000; Cova and Johnson 2002; Lo et al. 2004; Santos and Aguirre 2004; Chen 2008). In this approach, all evacuees are assumed to have the same physical, demographic, and perceptual attributes. Because information about evacuee characteristics, such as physical and psychological attributes, is not always available, this model is useful and easy to implement (De Silva and Eglese 2000; Cova and Johnson 2002; Lo et al. 2004; Santos and Aguirre 2004; Chen 2008).

In contrast to flow-based models, agent-based and cellular automata models depict evacuees as individuals rather than a continuous stream; thus, evacuation time is derived based on individual evacuee attributes. Input parameters, such as age, gender, fitness level, whether the evacuee is part of a group (e.g., a family), evacuee perception of a hazard, and locomotion speed (e.g., moving on foot or driving), are generally used in

these models to create a realistic depiction of evacuation (Yang et al. 2002; Varas et al. 2007; Yamamoto et al. 2007; Yuan and Tan 2007). To make these models more efficient and easy to implement, a generalized value (e.g., average) of each attribute is assigned to all evacuees rather than assigning unique values to each evacuee (Yang et al. 2002; Varas et al. 2007; Yamamoto et al. 2007; Yuan and Tan 2007).

Evacuation inherently involves movement through space during a certain time period. Depicting space and time is a strength of a geographic information system (GIS) (Cova 1999; Johnson 1999; Cutter 2003; Chen 2008). Due to the spatiotemporal nature of evacuation models and resulting outputs, implementing GIS-based evacuation models would facilitate the visualization of evacuation zone(s), evacuation routes, and locations of evacuees at various stages of evacuation (De Silva and Eglese 2000; Zou et al. 2006; Chen 2008; Cai et al. 2014). Such information could not only provide a clear and comprehensive understanding of the model as the evacuation progresses, but also could help with emergency response planning. However, despite recommendations to implement GIS-based evacuation models that would allow the visualization of the evacuation process and produce easily interpreted output maps (e.g., of evacuation zones, evacuation routes, or evacuee locations), as well as numerical outputs (e.g., total evacuation time), very few such models exist (De Silva and Eglese 2000; Zou et al. 2006; Chen 2008; Yassemi et al. 2008).

#### Cellular Automata Modeling

<span id="page-24-0"></span>Cellular automata is defined as a "discrete dynamical system whose behavior is completely specified in terms of a local relation" (Toffoli and Margolus 1987, 5) in which a space is represented as a grid of square cells of uniform size each containing a

small amount of data (i.e., objects). Time advances in discrete intervals (Toffoli and Margolus 1987; Batty 1997, 2007) such that at every time interval the state of each cell is evaluated based on the state of its neighboring cells, thus simulating change (Toffoli and Margolus 1987; Batty 1997, 2007). Cellular automata is used to model phenomena that are self-stimulating (e.g., biological cellular reproduction during wound healing), rather than relying on external stimulation to produce output (Batty 1997, 2007). Because this approach simulates local changes, it cannot be used to simulate neighborhood, zonal, and global changes that are not caused by local changes (Batty 1997, 2007). Some of the phenomena that are modeled using cellular automata are urban growth, fire spread, pedestrian and vehicle movement, and pedestrian evacuation (Ward et al. 2003; Dijkstra et al. 2006; Yue et al. 2007; Yassemi et al. 2008; Tonguz et al. 2009).

Although widely used in evacuation modeling, cellular automata models rarely incorporate evacuee characteristics. Joo et al. (2013) is one of the few studies that did so; evacuees' perceptions of a fire was used to determine their evacuation route choices in a cellular automata pedestrian evacuation model for a generic warehouse. The model used a cell size of 0.8 by 0.8 meters and a time step of 0.4 meters per second (Joo et al. 2013). The two evacuee perceptions that were modeled included: (1) evacuees who decided to evacuate because they perceived that the fire existed or that other evacuees were exiting the building and (2) evacuees who decided to evacuate selected their evacuation routes by examining the bordering the cell indicating their current location. If the evacuees perceived that the border cells were: (1) unoccupied by either other evacuees or the fire and (2) in the direction of an exit (i.e., the model assumed that the evacuees knew the

layout of the warehouse and exit locations), then they considered these cells as potential steps along their evacuation routes.

This perception-based decision-making process allowed evacuees to choose the shortest routes out of the warehouse. Because evacuee locomotion speed remained constant at 0.8 meters per second, the shortest route was also the fastest route. The authors tested the model with different combination of evacuee numbers (10, 50, and 100) and number of exits (1, 2, and 4). The results revealed that (1) both the number of evacuees and number of exits impacted evacuation time and (2) evacuation time decreased with increase in number of evacuees, which could be because there were more evacuees to initially perceive the fire, thus speeding up the process of noticing that evacuation was necessary. The authors also indicated that there may be an optimal number of evacuees required to decrease evacuation time and that additional evacuees beyond this optimal number may increase evacuation time due to congestion at exits. To more realistically represent evacuee behavior during an evacuation, the authors recommended using physical (i.e., age, gender, physical fitness) and psychological attributes of evacuees (in addition to the perception attributes used in their model).

#### Agent-Based Modeling

<span id="page-26-0"></span>An agent-based model is used to model systems that are driven by the behavior of autonomous agents, which are discrete entities (e.g., individual people, vehicles, drivers of vehicles, cells in the human body, or animals) with individual user-defined characteristics, behaviors, goals, and rules for interacting with other agents and the environment (Bonabeau 2001; Macy and Willer 2002; Macal and North 2009; Agent-Based 2010; Laver and Sergenti 2012). An agent may also have the ability to "learn"

from its environment and previous actions, thus changing selected behaviors and interaction rules (Caldwell 1997; Macal and North 2009; Agent-Based 2010). Because there is no centralized mechanism to control agent behavior, and since agents make decisions based on their immediate environment without the ability to "think" or "reason" strategically, agent-based modeling is ideal for examining events that evolve due to the actions of heterogeneous entities responding to their immediate environments, such as evacuation due to a fire (Caldwell 1997; Macy and Willer 2002; Macal and North 2009; Laver and Sergenti 2012). Like cellular automata, agent-based models are used to model phenomena resulting from local changes in which agents move along a grid at discrete time intervals (Caldwell 1997; Macy and Willer 2002; Parisi and Dorso 2005; Chen 2008; Macal and North 2009; Laver and Sergenti 2012).

Agent-based models have been used to predict many phenomena, such as sociological theories, pedestrian, and vehicle movement (including evacuation), and stock market trading (Epstein and Axtell 1996; Alfarano et al. 2005; Chen 2008; Ha and Lykotrafitis 2012). For example, the SugarScape model - an early agent-based model – examined human group formation and dissipation during diverse social processes, including birth, death, illness, and wealth accumulation (Epstein and Axtell 1996). In the initial model, (1) each agent (i.e., a person) moved from cell to cell, one cell at a time, to an unoccupied neighboring cell in any direction to gather sugar, and (2) only one agent could occupy each cell at a time (Epstein and Axtell 1996). In later versions of the model, agents were assigned demographic attributes (e.g., age, gender, economic and status, health condition) and cultural traits that influenced their ability to move to gather sugar. These attributes could be used to form specific groups (e.g., by gender or age), each with

homogeneous attitudes that influenced its movement and sugar-gathering behavior. The demographics of the groups formed by this model reflected social theories and cultural values of the time period.

Ha and Lykotrafitis (2012) created a pedestrian agent based evacuation model to explore the effects of interior doorway width, main exit doorway width, locomotion speed, and friction coefficient (i.e., the force between agents in contact with each other or with walls; in proportion to the relative tangential velocity between agents or between an agent and a wall) on evacuation time from one room (200 agents), two rooms (100 agents), one floor with six rooms (294 agents), and three floors each with six rooms (882 agents). The study revealed that: (1) faster locomotion speed can be used to represent panic; (2) higher friction coefficients resulted in slower evacuation times because evacuees required more time to move around each other when exiting; (3) wider interior room doorway widths and main exit doorway widths resulted in faster evacuation times due to less congestion at doorways; (4) main exit doorway widths affected evacuation time from multi-room structures; (5) the optimal locomotion speed range required to produce the fastest evacuation time varied based on interior room doorway widths, exit doorway widths, and the floor plan; (6) speeds below the desired speed (i.e., the speed assigned to all evacues for one run of the simulation ranged between  $1 \text{ m/s}$  and  $10 \text{ m/s}$ produced slower times because the agents were walking normally through the structure; and (7) speeds above the desired speed produced slower times because the agents became congested at interior doorways and the main exit doorway.

Chen (2008) developed an agent-based vehicle evacuation model to compare two evacuation scenarios for Galveston Island, TX: (1) all residents evacuated simultaneously and (2) residents were divided into geographic zones such that each zone exited at unique times (i.e., staged evacuation). The input parameters included road networks, duration for which a driver traveled at a specific speed, distance between stopped cars, distance a driver allowed between his/her vehicle and the preceding vehicle, vehicle deceleration time, speed differences between vehicles following each other, influence of distances between vehicles on vehicles' speed changes, vehicles' acceleration during speed changes, vehicles' acceleration from standstill, and vehicles' acceleration magnitude when their velocities were 80 kilometer per hour. The estimated average evacuation times for the two scenarios were 17 hours and 8 minutes and 16 hours and 39 minutes, respectively, with a time difference of 44 minutes, due to traffic congestion in the first scenario when all evacuees left at the same time.

#### Affordance Theory

<span id="page-29-0"></span>Developed by psychologist James J. Gibson and based on Gestaltist and Lewinian theories of behavior, affordance theory is a part of perceptual psychology that attempts to explain how people perceive their environments and act based on those perceptions (Gibson 1966, 1979). An individual determines the affordance of an object as helpful or harmful based on his/her perception and cognition of the object. Individuals derive affordances by perceiving characteristics of objects in their surroundings or of the surroundings themselves (e.g., size, shape, color, texture, motion, sound, scent, and distance from the individual) and assessing what opportunities the objects in their surroundings or the surroundings themselves can afford them. Then, individuals use these affordances to make decisions and take appropriate actions. For example, a hot pan on a stove may provide opportunities to cook and/or burn oneself. Thus, depending on past

experience with a stove, one may choose to carefully cook without burning oneself or to not cook because it is potentially harmful (Gibson 1966, 1979).

Although affordance theory informs human decision processes and behavior, it is rarely used when examining evacuation time. Because cellular automata and agent-based evacuation models allow inclusion of individual evacuee behavior, including their perceptions of a hazard (De Silva and Eglese 2000; Was 2005; Varas et al. 2007; Yuan and Tan 2007; Joo et al. 2013), Joo et al. (2013) developed a cellular automata evacuation model of a warehouse using affordance theory to determine the impact of perceptual attributes of evacuees on evacuation time. In the model, evacuees determined their evacuation routes by assessing the affordance of all grid cells adjacent to their locations and in the direction of the exit. Grid cells perceived to afford evacuation (e.g., along an evacuation route and clear of smoke and/or fire) were included in the evacuation routes. The study, however, did not compare evacuation times calculated with affordance attributes to times without them, thereby failing to determine the effect of affordance on evacuation time. However, it showed that affordance theory can be used in evacuation modeling to determine an evacuee's travel route choice based on his/her perception of the environment, the hazard, and past experience with the environment and hazard events.

#### Panic and Stampede Behavior

<span id="page-30-0"></span>Panic is related to an individual's response to an emergency situation based on his or her perception of the situation (LaPierre 1938; Quarantelli 2001; Mawson 2005; Pelechano et al. 2005; Zhang et al. 2007). Although the term "panic" has been used in academic research since the 1930's, it is not clearly defined (LaPierre 1938; Quarantelli 2001; Pelechano et al. 2005; Zhang et al. 2007). The earliest definition comes from

sociology, which considers panic to be any behavior that did not follow the instructions of emergency officials during an emergency situation, regardless of the following considerations: (1) whether the behavior was helpful or harmful to the individuals; (2) the individuals' mental states, emotions, or perception of the situations; and (3) whether officials were actually present to provide guidance (LaPierre 1938).

In psychology research, panic is defined as "inappropriate (or excessive) fear and/or flight and highly intense fear and/or flight" (Mawson 2005, 96). Subsequent definitions from sociology, psychology, and disaster research include groundless fear, irrational behavior, and flight behavior when an escape route is clearly present. However, there is no way to determine if the fear an individual experiences is "groundless", "excessive", "irrational", or "intense", and these terms are very subjective and can vary based on an individual's perception of a situation (Quarantelli 2001; Mawson 2005). Thus, what one person considers "groundless fear" or "irrational behavior" may be normal and logical to another person (Mawson 2005).

Due to lack of a clear definition, panic has seldom been used as an input parameter in pedestrian evacuation models. Even when panic was used, a definition to understand the effects it has on evacuation behavior and time is rarely provided (Pelechano et al. 2005; Hajibabai et al. 2007; Zhang et al. 2007). For example, in their pedestrian evacuation model of a generic building, Pelechano et al. (2005) divided evacuees into three categories: (1) individuals who knew the building layout and could handle stressful situations, (2) individuals who did not know the building layout and could handle stressful situations, and (3) individuals who did not know the building layout and could not handle stressful situations. "Stressful situation" was not defined,

although the authors indicated that the ability to deal with stress may vary based on an individual's natural abilities and/or job training (e.g., firefighting). The model assumed that individuals without such natural abilities or job training would not search for evacuation routes, and would panic and wait for instruction from those with the aforementioned abilities or training. However, panicked behavior was not further described; whether panicking simply meant waiting for others to find an evacuation route or engaging in other behavior while waiting was not clarified. The results indicated that evacuation times decreased when the evacuees consisted of a higher percentage of evacuees in the first two categories.

Zhang et al. (2007) created a pedestrian evacuation model of the Tianjin Olympic Center Stadium in Tianjin, China, most notably used for the 2007 [Fédération](http://www.fifa.com/)  [Internationale de Football](http://www.fifa.com/) Association (FIFA) Women's World Cup and the 2008 Olympic Games. The model examined the relationship between stadium egress width and evacuation time. Although the authors indicated the importance of including evacuees' psychological attributes in the model, they did not include panic because it was a complex psychological reaction that could not be accurately depicted via simulation.

Interviews with individuals who experienced and/or witnessed hazard events requiring evacuation, such as the 1977 Beverly Hills Supper Club fire, the 1979 crush at the Riverfront Coliseum in Cincinnati, OH, prior to a concert by The Who, the 1993 World Trade Center bombings, the 2001 World Trade Center terrorist attacks, and the 2005 London bombings, revealed that the primary behavior of the participants following a hazard event was to help other people escape and/or escape themselves without harming other individuals (Johnson 1987; Clarke 2002; Drury et al. 2009). The

participants indicated that very few people acted in a way that was irrational or harmful to themselves or others; rather, the shared hazard experience promoted comradery and teamwork so that everyone could reach safety.

Contributing to the discrepancy regarding the existence of panic during hazard events are the actions of government officials and news media (Johnson 1987; Clarke 2002). Government officials often suppress information about hazard events (e.g., the extent and/or severity of the hazard, lack of emergency management resources) because they assume that this information may cause panic among the individuals experiencing the event (Johnson 1987; Clarke 2002). Likewise, when reporting about hazard events, news media often assume that certain information may cause panic. Therefore, they often state that the outcome was better than expected because people surprisingly did not panic, thus assuming that panic is the normal reaction (Johnson 1987; Clarke 2002). However, based on the aforementioned research, this assumption is groundless. Because whether panic actually exists is unknown and a clear definition does not exist, it is not a useful construct to explain human behavior; thus, a common recommendation is to cease using it as a technical research term (Quarantelli 2001; Pelechano et al. 2005). As such, including panic as an input parameter in the evacuation model is beyond the scope of this research.

Similar to panic, human stampede behavior lacks a clear definition (Hseih et al. 2009; Burkle and Hsu 2011; Illiyas et al. 2013). It is rarely researched and is not included as a hazard category in the World Health Organization's Emergency Management-Disaster Database (EM-DAT; the most comprehensive disaster database in the world that can be searched by location, type of hazard event, or year) (EM-DAT 2009; Hseih et al.

2009; Burkle and Hsu 2011; Illiyas et al. 2013). Given the limited research conducted on this topic, most of which comes from the disciplines of public health and emergency management, and due to the lack of a definition, a stampede appears to occur when a large group of people move en masse in the same direction in extremely close proximity to one another in or towards a space that cannot hold or support all of them (Hseih et al. 2009; Burkle and Hsu 2011; Illiyas et al. 2013). Stampedes have occurred most often in Africa and Southeast Asia, usually during religious festivals (Burkle and Hsu 2011; Illiyas et al. 2013). However, they have also occurred at sports events, political protests, and music concerts Burkle and Hsu 2011). Rather than examining the social and psychological causes of stampedes, stampede-related research generally focuses on injuries people sustain as a result of experiencing stampedes and emergency mitigation and preparedness recommendations to reduce the risk and effects of stampedes (Hseih et al. 2009; Burkle and Hsu 2011; Illiyas et al. 2013).

Stampedes often begin during non-emergency circumstances, rather than in response to a hazard event (Hseih et al. 2009; Burkle and Hsu 2011; Illiyas et al. 2013). When exacerbated by environmental factors and emergency management policies that do not consider the possibility of a stampede, the stampede itself can develop into an emergency (Hseih et al. 2009; Burkle and Hsu 2011; Illiyas et al. 2013). For example, the 2009 stampede during FIFA World Cup Qualification Matches at the Félix Houphouët-Boigny Arena in Abidjan in the Republic of Côte d'Ivoire occurred due to poor crowd control, insufficient entrances and exits to the stadium, and filling the stadium past maximum capacity, thus leaving no room for people to move individually without being trampled or crushed in an emotionally-charged but (initially) non-emergency situation

(FIFA extends 2009; FIFA inquiry 2009). More recently, on February 8, 2015, a stampede occurred during a soccer match between the Zamalek and Engineering for the Petroleum and Process Industries (ENPPI) Clubs in a stadium owned by the Egyptian military in Cairo, Egypt, for the same reasons as the aforementioned 2009 stampede, as well as due to the hostility between fans of the opposing teams (Kirkpatrick and Thomas 2015; Maher and Mourad 2015). Because there is no specific definition of stampede available that can be used to parameterize it in an evacuation model (Hseih et al. 2009; Burkle and Hsu 2011; Illiyas et al. 2013), stampede behavior was not used as an input parameter in this research.

#### Blood Alcohol Concentration

<span id="page-35-0"></span>The effect of BAC on evacuation behavior and/or time has not been examined at the time of this research. However, several studies looked at the effects of drinking in a social environment on memory, decision-making, and risk-taking behavior (Lyvers and Maltzman 1991; Weissenborn and Duka 2003; George et al. 2005).

Lyvers and Maltzman (1991) examined the effects of social alcohol consumption on the frontal cortex of the brain, which governs higher cognitive functions, such as planning, decision-making, and understanding the consequences of one's actions. Participants were evenly divided into the following four groups using a random, doubleblind approach: (1) individuals who were told they had been given an alcoholic beverage and actually received one, (2) individuals who were informed that they had been given an alcoholic beverage, but received a placebo, (3) individuals who were told they had been given a placebo and placebo and actually received one, and (4) individuals who were informed that they had been given a placebo, but actually received an alcoholic beverage.
The alcoholic beverages consisted of tonic water mixed with vodka, which was sufficient to induce a BAC of 0.05% while disguising the taste of the vodka. The placebo consisted of tonic water only.

After the participants consumed their beverages, they took the Wisconsin Card Sorting Test twice. This test was a computerized examination in which participants sorted cards into one of four stacks based on color of the cards or the numbers or shapes on the cards. A chime sound indicated when a card was placed correctly and a buzzer sound indicated when a card was placed incorrectly. The participants did not know the sorting criteria in advance and figured it out by attempting to match colors, shapes, and numbers, and listening for the resulting sound. Multivariate analysis of variance (MANOVA) found that individuals who consumed alcoholic beverages performed statistically significantly more poorly than those who did not (alpha  $= 0.05$ ), suggesting that alcohol in social drinking quantities impairs processes governed by the frontal cortex of the brain, such as planning, decision-making, and understanding the consequences of one's actions. Although performance did not differ based on gender after consuming alcohol, the study revealed a practice effect for all participants (i.e., the scores of all the participants increased statistically significantly from the first run to the second, suggesting that their improvement was due to becoming more familiar with the task, rather than alcohol consumption).

George et al. (2005) also investigated the effect of social drinking on decisionmaking. Participants were divided evenly into two groups using a random, double-blind approach. One group was administered alcohol plus sufficient tonic water and Tabasco sauce to disguise the taste of the alcohol, while the other group was administered a

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placebo (tonic water and Tabasco sauce). After beverage consumption, the participants took the following three tests:

- 1. Matching Familiar Figures Task, developed by Carins and Cammock (1978): Participants were simultaneously shown a stimulus figure and six other figures. They were asked to identify which one of the six figures matched the stimulus figure. This matching process was performed 20 times. Participants were evaluated on the number of incorrectly matched figures, response time for the first attempt, and I score (i.e., index used to quantify impulsivity).
- 2. Rey Auditory Verbal Learning Test, developed by Rey (1964): Participants were given two lists of 15 unrelated words and asked to repeat the words without memory aids. This test evaluated short-term memory.
- 3. Decision-Making Task, developed by Rogers et al. (2003): Participants were shown two histograms (i.e., the "control and "experimental" histograms) each depicting binary-outcome gambles (i.e., probability of winning or losing; histogram height indicated the probability of winning). The control histogram always showed a 50% chance of winning or losing 10 points. The experimental histogram values varied; the chance of winning was either 33% or 66% and point value options were winning or losing 20 or 80 points, thus resulting in eight possible experimental histograms. Participants were asked to choose which histogram represented a more profitable probability. After performing eight trials, two of which depicted loss-only options (i.e., both the control and experimental histograms depicted losses), and two of which depicted win-only options (i.e., both the control and experimental histograms

depicted wins), the participants were told that the individual with most points at the end of the eight trials would receive an award of £10. The proportion of experimental gamble selection and time required to choose a histogram were used to evaluate the winners.

The results revealed no difference (statistically significant or otherwise) between the placebo and alcohol groups for the number of incorrectly matched figures, response time for the first attempt, I score from the Matching Familiar Figures Task or short-term memory from the Rey Auditory Verbal Learning Test. On the Decision-Making Task, analysis of variance (ANOVA) with an alpha value of 0.05 revealed that participants in both groups always chose the experimental histogram when the probability of winning was high and always chose the control histogram when it was low. Similarly, participants in both groups always chose the experimental histogram more often when the potential number of points to win was high and chose the control histogram when it was low. The decision time for both groups was statistically significantly faster when the probability of winning was high and/or the expected point gain was large. It was statistically significantly slower for both groups when the probability of winning was low and/or there was an expected point loss. Participants in both groups chose the control histogram statistically significantly more often during win-only situations rather than during lossonly situations.

These results indicated that, in general, social drinking did not influence impulsive behavior, short-term memory, risk-taking behavior, risk-aversion behavior, or time required to make decisions regarding risks. However, regardless of the magnitude of the potential losses, the alcohol group chose the experimental card in the DecisionMaking Task slightly (i.e., not statistically significantly) more often than the placebo group when the probability of a gain was high rather than low, the number of points to be obtained was large rather than small, or when they thought they would win the £10. Thus, individuals who were drinking socially may not be able to distinguish between the probability of a gain and how many points they may obtain, particularly when the probability of a loss is high.

Weissenborn and Duka (2003) examined the effects of social drinking on working memory, problem-solving, and decision-making. Participants took the following four tests to evaluate cognitive function twice; once after drinking a beverage consisting of tonic water, Tabasco sauce, and sufficient alcohol to induce a mean BAC of 0.60 g/L, and on another day after drinking a placebo beverage consisting of tonic water and Tabasco sauce sufficient disguise the taste of the alcohol:

- 1. Cantab Tower of London, developed by Owen et al. (1990): In this computerbased test, a computer screen was divided in half horizontally. The top half contained three colored balls arranged in a pattern, while the bottom half contained three colored balls not arranged in a pattern. Participants moved the balls in the bottom half to match the pattern in the top half as quickly as possible and using as few ball moves as possible.
- 2. Cantab Spatial Working Memory Task, developed by Owen et al. (1990): Participants were presented with groups of four, six, or eight boxes with tokens inside them (Owen et al. 1990; Weissenborn and Duka 2003). The goal was to locate the box containing a blue token. Participants performed this task repeatedly, with the instruction that a box that contained the blue token in past

searches would not contain it again. Participants were evaluated on whether they searched a box that previously contained the blue token, whether they searched the same box twice within the same trial and the order in which they searched the boxes (the same order for all trials was ideal).

- 3. Cantab Pattern Recognition, developed by Morris et al. (1987): Participants viewed several geometric patterns sequentially over three seconds. Five seconds after viewing the series of patterns, participants were shown another two geometric patterns, one of which they had just viewed in the previous sequence. Participants were then asked to indicate which of the two patterns was in the series they initially viewed. This matching exercise occurred 12 times. Participants were scored based on the number of correct matches and response time for each correct match.
- 4. Cantab Spatial Recognition, developed by Morris et al. (1987): Participants were shown five empty boxes in different locations on a computer screen. Five seconds after that, participants were simultaneously shown two boxes: (1) one box located at the same place on the screen as one of the previous five boxes and (2) one box located at a place that was unoccupied by any of the previous five boxes Participants were required to indicate which of the two boxes was located at a place previously occupied by one of the five boxes. They performed this task four times and were scored based on number of correct responses and time required to indicate a correct response.

A random, double-blind approach was used to determine whether the participants' alcohol consumption occurred on the first or second administration of all the tests

(Weissenborn and Duka 2003). MANOVA (alpha  $= 0.05$ ) revealed that the alcohol group performed statistically significantly more poorly than the placebo group on the Cantab Spatial Recognition Test, but there was no difference between the groups on the other tests. Evidently, social alcohol consumption may impair spatial recognition but not pattern recognition or working memory.

The findings by George et al. (2005) that individuals drinking socially may not be able to distinguish between the probability of a gain and how many points they may obtain, particularly when the probability of a loss is high, coincided with Lyvers and Maltzman's (1991) earlier finding that alcohol in social drinking quantities impairs processes governed by the frontal cortex of the brain. The finding by George et al. (2005) that social alcohol consumption did not affect working memory coincided with the findings of Weissenborn and Duka (2003).

## Summary

Since the 1980s, evacuation models have been developed for both anthropogenic and natural hazard events using flow-based, cellular automata, and agent-based models. Although these models depict pedestrian and vehicular movements, they rarely use affordance theory, which captures human perception of the environment and explains decision-making processes and subsequent behavior that ultimately influences evacuation route choice and evacuation time. Furthermore, models integrating both pedestrian and vehicular movements are almost non-existent. In this study, pedestrian and vehicular movements were combined to determine optimum evacuation time from a university football stadium and its surrounding campus to determine the variability of evacuation time due to evacuees' physical and psychological attributes. An agent-based model using

physical (age, gender, physical fitness, and BAC) and psychological attributes (prior experience attending USM football games, evacuating from large, outdoor public places, and with hazard events) of evacuees was implemented to determine optimum and maximum evacuation times for football game attendees to exit the M.M. Roberts Stadium at USM and drive their vehicles off the campus. Because this is one the few studies to combine modeling pedestrian and vehicular evacuation along with evacuee behavior, this research contributes to the broader literature of evacuation by providing insights into the impact of evacuee characteristics on evacuation time and identifying specific physical and psychological characteristics of evacuees that influence evacuation time.

## CHAPTER III - METHODOLOGY

## **Overview**

In this chapter, a description of the study site is provided, followed by a discussion of scales of analysis, data sets and data collection techniques, statistical and geospatial techniques used for data processing, and the model implemented to compute evacuation time. Because physical and psychological characteristics of evacuees impact their movement, agent-based modeling and affordance theory were used to model evacuation time. A mixed-methods approach using quantitative and qualitative data was implemented to accomplish this research. A causal research design was employed to understand the impact of evacuee characteristics (independent variables; age, gender, BMI, BAC, and football game evacuation affordance attributes: prior experience attending USM football games, evacuating from large, outdoor public places, and with hazard events) on evacuation time (dependent variable). Statistical analyses (e.g., ANOVA, regression) were implemented to analyze the variation in evacuation time due to changes in values of independent variables and also to determine the variables impacting evacuation time.

#### Study Site

The M.M. Roberts Stadium, situated at USM's main campus in Hattiesburg, MS, is the home of USM's football team (Figure 2). According to the USM Ticket Office, the stadium's maximum capacity is 36,000, which includes 4,148 student section seats and 11,000 season ticket holder seats. It usually hosts five to seven home games per season. Fan attendance per game varies due to home team rankings, opponent rankings, rivalries, game time, game day weather, whether the game is televised, and fans' opinions of

players and coaches (Kittrell and Thompson 2009; Zale 2010). The USM Department of Parking Management revealed that, for the 2015 football season, 3,429 parking spaces on campus were reserved for season ticket holders, while the remaining parking spaces were used by game attendees who did not have season tickets. This study site was selected because it was used in previous evacuation modeling research conducted by the NCS4 and Oak Ridge National Laboratory (ORNL) (Jones et al. 2009; Zale 2010; Pedestrian Dynamics 2017), which enabled comparison of results from this study with previous findings.



*Figure 2.* Map of the study site.

# Scales of Analysis

Social: The social scale of analysis is an individual evacuee for the pedestrian portion of the model (i.e., evacuees move on foot from their stadium seats to their vehicles or mobile triage areas) and an individual vehicle for the vehicle portion of the model (i.e., vehicles moved from parking spaces or mobile triage areas to campus exit points).

• Spatial: Zale (2010) found that 2.5 meters by 2.5 meters cell size or coarser resolution resulted in an inaccurate depiction of the spatial extent of the stadium in comparison to a 1 meter by 1-meter color infrared image. To maintain accuracy, a spatial resolution of 1.5 meters by 1.5 meters was used.

## Data Collection

Primary and secondary data were used in this research (Table 2). Numerous secondary data sets were collected; the first eight were spatial and the remainder were non-spatial. Primary data were collected using the USM Football Game Attendee and Tailgater Questionnaire, a paper-based survey instrument (Appendix C) that included items pertaining to evacuees' psychological and physical attributes and football game affordance attributes. Vehicle attributes, including vehicle speed (i.e., the average campus speed limit of 20 miles per hour obtained from USM's Police Department (UPD) (Kittrell and Thompson 2009) and average number of people per vehicle traveling to football games at USM) were collected from the USM Ticket Office and via the questionnaire. After receiving approval from USM's Institutional Review Board (IRB) (Appendix B), the questionnaire was administered prior to USM's home football game versus the University of North Texas on October 9, 2015 (5 p.m. kickoff). Per the USM Athletic Department and Dr. Lou Marciani (from the NCS4), this game represented the "average" or "normal" football game audience at USM.

*Data Sets*



Table 2 (continued).



To administer the questionnaire, twelve USM students were recruited via (i) inperson and electronic communication with students in USM's Department of Geography and Geology, (ii) an advertisement in USM Talk (i.e., a listserv subscribed by individuals in the USM community), (iii) announcements at meetings of the USM Sport Management Club (i.e., an academic and pre-professional student organization), and (iv) an email to members of the USM chapter of Women in Science and Engineering. USM's Athletic Department indicated that few, if any, tailgaters would be on campus before 2 p.m. for an "average" game with 5 p.m. kickoff. They also required the questionnaire must be administered outside the stadium only and that administration must cease by 5 p.m.

Prior to survey administration, the surveyors were given an explanation of each item on the questionnaire. They were also told to (1) inform each participant of the approval of this study by the USM Institutional Review Board and the USM Athletic Department, and of their right to not participate or to stop participating at any time; and (2) not collect personal identification information from any participants.

From 2 p.m. to 4:45 p.m., the surveyors walked around the campus in common tailgating areas and invited tailgaters to complete hard copies of the questionnaire. The survey was administered to 361 individuals (1 % sample of the maximum stadium capacity of 36,000). This 1% sample was selected by purposive random sampling and per the recommendation of Jones et al. (2009), who collected a sample of 1.31% of the stadium population when conducting a questionnaire-based survey at the same location using the same methodology. Cunningham et al. (2009) also employed this sampling strategy at a National Association for Stock Car Auto Racing (NASCAR) event.

Although this convenience sampling strategy could potentially result in bias because individuals who are easy to contact often represent only a small portion of the total population (Montello and Sutton 2013), the USM Athletic Department indicated that the majority of the football game attendees were tailgating on the USM Hattiesburg Campus prior to the football game. Individuals who were on campus prior to the game but not tailgating, such as university staff, security personnel, and food service workers, were identified by their name badges, and/or uniforms, and were not surveyed.

## Data Processing

The hard copy questionnaire response data were manually entered into SPSS 22. Frequency analysis was conducted on all questionnaire items to address erroneous

responses or incorrectly coded information. From these data, BAC and BMI were calculated (Appendices D and E, respectively). The age variable was recoded into the following age groups identified by the U.S. Census Bureau: 18 through 25 years of age, 26 through 35 years of age, 36 through 45 years of age, 46 through 55 years of age, 56 through 65 years of age, and 66 years of age and greater (Summary n.d.).

All geospatial data sets were converted to North American Datum 1983, Universal Transverse Mercator, Zone 16 North. The campus sidewalks and the road network shapefiles were checked for accuracy against the one-meter color infrared image of Forrest County and by driving and biking around the campus. Minor digitization adjustments were made to both layers due to new construction on the campus.

Speed limit, maximum road capacity in vehicles per hour, and number of lanes for major roads in the study area (i.e., U.S. Highway 49, Hardy Street, North 38<sup>th</sup> Avenue, and parts of West 4<sup>th</sup> Street) were obtained from the Mississippi Department of Transportation and added to the attribute table of the road network file. The number of lanes and speed limits of campus roads were obtained by driving and biking around the campus and were also added to the attribute table. Finally, with help from the USM Department of Parking Management, the parking lot locations and number of parking spaces assigned to football game attendees were determined. The shapefile representing these parking lots was created by digitizing each feature from the 2012 one-meter image of Forrest County, using the 2015 parking map as a reference. The number of parking spaces in each lot was stored as an attribute in the parking lot shapefile.

#### Model Implementation

This section covers the steps employed to implement the model (Figure 3). First, the number and spatial distribution of evacuees, followed by their modes of transportation and locomotion speeds, were determined. Next, the evacuation time for each segment of the model and total evacuation time (i.e., time required for all evacuees to move from their stadium seats to an evacuation exit point) were calculated. Finally, the accuracy of the computed evacuation times was assessed.

#### *Step 1: Determine the Number and Spatial Distribution of Evacuees*

In this research, the following two assumptions were made: (1) the hazard event directly impacts the football stadium, requiring its total evacuation and (2) the game will end immediately following the hazard requiring the fans to clear the area. Therefore, the immediate impact zone used was the football stadium and the extended impact zone was USM's Hattiesburg Campus.

The model was implemented for a worst-case scenario, in which the stadium is occupied to its fullest capacity (i.e., 36,000 evacuees). The evacuees were assumed to be in their seats at the beginning of the evacuation. Although in reality, they may be in other locations (i.e., concessions or the restrooms), knowing which or how many evacuees were not in their seats and where they were located instead was not possible. Thus, their seats were used as their origin locations for the evacuation. The hazard event impacting the stadium was unknown; thus, the model assumed that all stadium exit corridors, roads, and sidewalks were functional during the evacuation.

Initially, to facilitate comparison of results to a previous evacuation model of the same audience and location (Zale 2010), evacuees were divided into those who required

immediate medical attention and those who did not. According to the local ambulance service, evacuees who needed immediate medical attention would walk or be carried from the stadium to a mobile triage location and then moved by ambulance to one of the two hospitals (Carter 2009). A stadium security expert determined that a hazard event severe enough to necessitate mobile triage would most likely result in 50 evacuees who needed immediate medical attention (McGee 2009). Because 50 evacuees was only 0.14% of the total audience number (i.e., 36,000 evacuees), the mobile triage component of the model was removed and all evacuees were assumed to be uninjured (Figure 3).



*Figure 3.* Revised evacuation model diagram.

*Determine Evacuees' Modes of Transportation*. Before implementing the model, the evacuees' modes of transportation were determined based on the survey data, which revealed that 73.45% of participants drove to games, 25.71% walked, and 0.85% biked. These percentages were applied to the 36,000 fans in the stadium to determine the number for evacuees using each mode of transportation (Table 3).

Mode of Transportation	Questionnaire Response Frequency	Questionnaire <b>Response Percent</b>	Stadium Population
Drive	260	73.45	26,441
Walk	91	25.71	9,254
<b>Bike</b>	3	0.85	305
Total	354	100.00	36,000

*Evacuees' Modes of Transportation*

USM's Department of Parking Management and UPD indicated that the travel routes of cyclists on campus are neither closely monitored nor are cyclists required to park their bicycles at bicycle racks. Furthermore, cyclists on the campus tend to ride through grassy areas as well as on roads, sidewalks, and bike paths. Thus, knowing where their evacuations would begin (i.e., where they parked) and the evacuation routes they would take was not possible. Therefore, in order to maintain the survey data ratio of participants' mode of transportation, two of the three survey participants (i.e., 0.85% of evacuees who used bicycles) were added to the number of participants who indicated they drove and one was added to the number participants who indicated they drove (Table 4).



## *Extrapolated Modes of Transportation*

Analysis of the questionnaire data, interviews with UPD personnel, and examination of the data and methodology of a similar survey administered to tailgaters, revealed that most fans drove to games in groups of four people per vehicle (Jones et al. 2009; Kittrell and Thompson 2009). Thus, the number of evacuating vehicles used in the model was 6,661 (i.e., the extrapolated number of the audience who drives to the stadium divided by four; 26,644 people / 4). According to the USM Ticket Office, 7,655 parking spaces were available to football game attendees. Only season ticket holders (i.e., 11,000 stadium seats) had reserved parking spaces on campus; attendees who did not have season tickets could park in any of the spaces that were not reserved. Associating a stadium seat with a parking space was not possible because 25,000 attendees (i.e., 69.44%) did not have season tickets and the USM Ticket Office would not disclose season ticket holder seat and parking assignments. Therefore, parking spaces were randomly assigned to evacuees as explained later in this chapter.

*Average Locomotion Speeds (m/s)*



The age data provided by survey participants were categorized based on the U.S. Census Bureau's classification discussed previously: 18 through 25 years, 26 through 35 years, 36 through 45 years, 46 through 55 years, 56 through 65 years, and 66 or more years (Summary n.d.). Because this classification did not match that of Carey (2005, 2), and because older individuals walk more slowly than younger individuals, survey participants whose indicated ages were in the first four age groups (i.e., 18 through 25 years, 26 through35 years, 36 through 45 years, and 46 through 55 years) were considered "younger", while those in last two age groups (i.e., 56 through 65 years and 66 or more years) were considered "older". The percentages of younger male, younger female, older male, and older female survey participants were applied to the stadium population (i.e., 36,000 evacuees) to determine the number of evacuees in each age group and their corresponding locomotion speeds. For example, 148 survey participants (i.e., 43.53%) indicated that they were 55 years of age or less and male (i.e., in the younger male category); therefore, 43.53% of the stadium population (i.e., 36,000 evacuees \* 0.4353), or 15,670.59 evacuees, were assigned the younger male locomotion speed of 1.51 meters per second from Table 5. The same calculations were performed for the

remaining three locomotion speed groups, and since the number of evacuees cannot be fractional in reality, the results were rounded to the nearest whole number (Table 6).

Table 6

	*Number of Survey Participants	Percentage of Survey Participants	Number of Evacuees	Locomotion Speed $(m/s)$ from Carey (2005)
<b>Younger Male</b>	148	43.53%	15,671	1.51
Younger Female	163	47.94%	17,259	1.44
Older Male	16	4.71%	1,694	1.38
<b>Older Female</b>	13	3.82%	1,376	1.22
Total	340	100.00%	36,000	n/a

*Evacuee Locomotion Speed Assignments*

\*Number of survey participants who responded to the age and gender questionnaire items.

## *Step 2: Determine Evacuation Times*

The evacuation routes connected the initial locations of evacuees with their destinations (i.e., the road and sidewalk network exit points). All open, walkable areas present on the campus (e.g., sidewalks, green space, cutting through campus buildings, parking lots) were considered as potential evacuation routes for evacuees who moved on foot from the stadium to their vehicles (in the parking lots) and for those who exited entirely on foot. The existing road networks surrounding the campus were considered as

evacuation routes for evacuees driving from the parking lots to the road network exit points.

Results from statistical analyses of the survey responses (discussed in Chapter IV) were used to determine significant attributes impacting their evacuees' evacuation behavior, which were subsequently used as input parameters in the agent based evacuation model. Frequency analysis of survey data revealed that 61.3% of the participants indicated that they had previously experienced a hazard event and 79.7% of these respondents indicated it was a hurricane. The impact areas of tropical storms and hurricane impact are predicted days in advance, and according to USM's Athletic Department and UPD, football games potentially occurring during a hurricane would be canceled prior to its onset, thus eliminating the possibility of any evacuation. Therefore, football game affordance attributes (i.e., an evacuee's prior experience with hazard events, attending football games, and evacuating from large, outdoor public places) were not included in the model.

The physical attributes of evacuees impacting their movement within the stadium, and subsequently evacuation time from the stadium, were age group and gender. BAC and BMI were also considered as potential input parameters. However, as explained in Chapter II, the effects of BAC on locomotion speed and/or evacuation time has not been examined. Carey (2005) also did not discuss the effects of BMI or BAC on locomotion speed. A series of linear regressions was used to examine the predictive relationship between walking speed (i.e., the dependent variable) and gender, age group, BMI, and BAC (i.e., the predictors). A statistically significant relationship was not found when

BMI and BAC were included; thus, only age group and gender were used to determine locomotion speed in the model (Appendix G).

Total evacuation time was calculated starting when the order to evacuate the stadium was given and ending when the evacuation zones were empty of evacuees. Pedestrian Dynamics, the agent-based simulation software package used to create NCS4's evacuation model of the M.M. Roberts Stadium, was employed to compute pedestrian evacuation time for the following reasons: (1) using the same software facilitated comparison of the results of this project to previous evacuation models (i.e., Pedestrian Dynamics 2017) and (2) the researcher had access to the source code; thus, the modification of the software as needed beyond average user capabilities was possible.

Three nested Bernoulli distribution functions were used to assign the locomotion speeds from Table 6 to the agents in the Pedestrian Dynamics software. The Bernoulli distribution represents the probability that a random variable will have one of two values (Uspensky 1937). For example, in a coin toss with an unweighted and two-sided coin, heads can be assigned a value of 0 and tails can be assigned a value of 1. Thus, there is a 50% probability that the coin will land with heads up (i.e., a value of 0); otherwise, the coin will land with tails up (i.e., a value of 1) (Uspensky 1937). However, a 50% probability would not work in this model as there were four locomotion speeds (Table 6). Pedestrian Dynamics software allowed using percentages other than 50% in its Bernoulli distribution function, so it was modified to represent the percentages in Table 6.

Pedestrian Dynamics uses a proprietary scripting language called 4DScript (Pedestrian Dynamics 2017). The code syntax for one Bernoulli distribution function was Bernoulli  $(a, b, c)$ , where  $a =$  the percent probability that the assigned value is  $b$ , else the

assigned value is *c*. Since the model contained four locomotion speeds, the functions were nested such that the value for *c* was the beginning of the next Bernoulli distribution function. The functions evaluated the locomotion speed assignment probability in order of highest to lowest based on the percentage of survey participants from Table 6 (i.e., younger female, younger male, older male, older female). This order was selected because the survey participant percentages already reflected the inherent probability in choosing an evacuee with specific age group and gender characteristics (e.g., younger and female).

The syntax for the nested Bernoulli functions was Bernoulli(47.94, 7, Bernoulli(83.62, 1, Bernoulli(55.18, 6, 8))), where  $47.94$  = the percentage of younger female survey participants,  $7 =$  the numerical code assigned by the software to assign a locomotion speed of 1.44 meters per second (i.e., the younger female locomotion speed from Table 6),  $83.62$  = the percentage of younger male survey participants when younger female participants were excluded from the total number of survey participants,  $1 =$  the numerical code assigned by the software to assign a locomotion speed of 1.51 meters per second (i.e., the younger male locomotion speed from Table 6), 55.18 = the percentage of older male survey participants when younger female and younger male participants were excluded from the total number of survey participants,  $6$  = the numerical code assigned by the software to assign a locomotion speed of 1.38 meters per second (i.e., the older male locomotion speed from Table 6), and  $8 =$  the numerical code assigned by the software to assign a locomotion speed of 1.22 meters per second (i.e., the older female locomotion speed from Table 6).

*Calculate Evacuation Time Segments*. The evacuation model was divided into two segments. The first segment consisted of the evacuees traveling on foot from their seats in the stadium to the stadium gates (i.e., within the stadium). The second segment had two simultaneously occurring components: (1) evacuees who drove to the game moved on foot from the stadium gates to their vehicles in parking lots and drove off the campus, ending at intersections of campus roads with city roads; and (2) evacuees who walked to the game moved on foot from the stadium gates to intersections of campus sidewalks with city sidewalks (Figures 4 and 5).



*Figure 4.* Evacuation segments.





Segment 1 of the model was run 15 times (Parisi and Dorso 2005; Chen 2008), for each of three previously explained locomotion speed conditions: (1) locomotion speeds from Table 6 based on the survey data; (2) a locomotion speed of 1.5 meters per second; and (3) locomotion speed determined by a triangular distribution with minimum, mode, and maximum locomotion speeds of 0.8 meters per second, 1.35 meters per second, and 1.75 meters per second, respectively. However, while trends in evacuation time for each locomotion speed condition were somewhat visible after 15 runs, some results appeared to be outliers (i.e., underestimating the number of evacuees by more than 20 and/or overestimating the evacuation time for all the evacuees by more than 90 seconds outside of the main grouping of evacuation times). Therefore, to obtain at least 20 non-outlier runs for each locomotion speed condition, the model was run 15 additional times for each

locomotion speed condition, for a total of 30 times per condition. A review of the results revealed that the second and third locomotion speed conditions had 28 and 27 non-outlier runs, respectively. However, the first locomotion speed condition had only 20 non-outlier runs. Thus, the first locomotion speed condition was run ten additional times, finally producing 28 non-outlier runs.

Initially, both components of the second segment of the model were going to be implemented with Pedestrian Dynamics. However, later it was discovered that the software was incompatible with the polyline shapefiles needed to implement network analysis for vehicle evacuation on roads and pedestrian evacuation on sidewalks. Therefore, an alternate approach was implemented to model these stages of the evacuation.

For the first component of the second segment, the 26,644 driving evacuees moved from the stadium to parking lots and then from parking lots to 48 road network exit points (i.e., campus and city road intersections). There were 22 stadium exits and 56 parking lots, resulting in 1,232 potential stadium exit to parking lot combinations. Knowing the location of each evacuee's vehicle within its parking lot and which gate and parking lot each evacuee would choose in a real evacuation was not possible. The following steps were used to calculate the evacuation time for this portion of the model (data sets, example calculations, and intermediate results are presented in Appendix I):

1. The Euclidean distance between the centroid of the stadium and that of each parking lot (i.e., 56 distances) was measured using the Near Tool in ArcGIS.

- 2. Minimum, mean, and maximum locomotion speeds for survey participants who indicated that they drove to games (i.e., car/truck/van or RV/motorhome responses to questionnaire Item 9) were calculated.
- 3. The minimum, mean, and maximum travel times for each of the 56 stadium centroid to parking lot centroid distances (i.e., Step 1 results) were calculated by dividing each distance by the minimum, mean, and maximum locomotion speeds from Step 2, as well as a locomotion speed of 1.5 meters per second (e.g., minimum travel time for distance  $#1 =$  distance  $#1 /$  minimum locomotion speed; see Table A5, fields  $t_s$  1  $-26$ ,  $t_s$  1  $-46$ ,  $t_s$  1  $-51$ , and t s 1 5, in Appendix I for examples and intermediate results).
- 4. The minimum, mean, and maximum travel times for this component (i.e., all of the stadium centroid to parking lot centroid distances) were calculated from the results of Step 3 (i.e., the minimum, mean, and maximum travel times based on all of the distances for each speed).
- 5. The number of driving evacuees (i.e., 26,644) was divided by the number of parking lots (i.e., 56) to determine the number of evacuees per lot (i.e., 475.79 evacuees rounded to 476, as fractional numbers of people are not possible). Although this number was likely, not true in reality, there was no way to know how many evacuees parked in each lot, so the evacuees were evenly distributed among all of the lots. The model assumed that each group of 476 evacuees left simultaneously. Again, this may not be true in reality, but knowing the exact time each evacuee left was not possible.
- 6. Most people walk two to three abreast when in groups, even if the group contains more than two to three individuals (Costa 2010). This creates a crowd density of approximately three people per square meter, which is the most common density for urgent, purposeful walking in evacuations (Still 2014). To create this density while calculating travel time for each group of 476 evacuees, first, 476 was divided by three to determine the how many groups of three people abreast were in each of the 56 groups of 476 evacuees (i.e., 158.67 rounded to 159).
- 7. The model assumed that each of the 159 groups of three evacuees abreast from Step 6 left the stadium at one-second intervals. Thus, the minimum, mean, and maximum evacuation times for each group of 476 evacuees were calculated by adding the respective minimum, mean, and maximum travel time (calculated in Step 4) for the minimum, mean, and maximum locomotion speeds (i.e., from Step 2) to 158 (i.e., 159 groups of three evacuees abreast – 1; the first group of three evacuees required the minimum, mean, or maximum travel time from Step 4 to evacuate, and each subsequent group left at oneminute intervals afterward, so one minute for each subsequent group was added to the respective minimum, mean, or maximum travel times).

Knowing which routes and road network exit points drivers would choose in an actual evacuation was not possible; thus, the vehicles were evenly distributed among each road network exit point. The evacuation time for the 6,611 evacuating vehicles to drive from the 56 parking lots to one of the 48 road network exit points (e.g., campus and city road intersections) was calculated using the following steps:

- 1. The New Closest Facility function in the Network Analyst Extension of ArcGIS was used to determine the travel times from the parking lots to the road network exit points.
- 2. The minimum vehicle evacuation time was calculated using the following equation: (number of evacuating vehicles/number of road network exit points) \* minimum travel time from Step 1.
- 3. The maximum vehicle evacuation time was calculated using the following equation: (number of evacuating vehicles/number of road network exit points) \* maximum travel time from Step 1.
- 4. The average vehicle evacuation time was calculated using the following equation: (number of evacuating vehicles/number of road network exit points) \* average travel time from Step 1.

The second component of the second segment modeled the 9,356 evacuees moving on foot from the stadium to the sidewalk network exit points (i.e., campus and city sidewalk intersections). There were 22 stadium exits and 66 sidewalk network exit points, resulting in 1,452 potential stadium exit to sidewalk network exit point combinations. Similar to the first component, knowing which gate and sidewalk network exit point each evacuee would choose in an actual evacuation was not possible. Although evacuees may move on sidewalks, they may also cut through buildings and across parking lots and other open spaces while moving from the stadium to the sidewalk network exit points; thus a nearly infinite number of walking routes were available. Thus, the following steps were used to calculate the evacuation time for this portion of the

model (data sets, example calculations, and intermediate results are presented in Appendix J):

- 1. The Euclidean distance between the stadium centroid and each sidewalk network exit point (i.e., 66 distances) was measured using the Near tool in ArcGIS.
- 2. Minimum, mean, and maximum locomotion speeds for survey participants who indicated that they walked to games (i.e., walk responses to questionnaire Item 9) were calculated.
- 3. The minimum, mean, and maximum travel times for each of the 66 stadium centroid to sidewalk network exit point distances (i.e., Step 1 results) were calculated by dividing each distance by the minimum, mean, and maximum locomotion speeds from Step 2, as well as a locomotion speed of 1.5 meters per second (e.g., minimum travel time for distance  $1 =$  distance  $1 /$  minimum locomotion speed; see Table A7, fields  $t_s = 1_44$ ,  $t_s = 1_47$ ,  $t_s = 1_51$ , and t\_s\_1\_5, in Appendix J for examples and intermediate results).
- 4. The minimum, mean, and maximum travel times for this component (i.e., all of the stadium centroid to sidewalk network exit point location distances) were calculated from the results of Step 3 (i.e., minimum, maximum, and average travel times based on all of the distances for each speed).
- 5. The number of walking evacuees (i.e., 9,356) was divided by the number of sidewalk network evacuation points (i.e., 66) to determine the number of evacuees per lot (i.e., 141.76 evacuees rounded to 142, as fractional numbers of people are not possible). Although this number was likely not true reality,

there was no way to know how many evacuees exited via each sidewalk network exit point, so the evacuees were evenly distributed among all of the points. The model assumed that each group of 142 evacuees left simultaneously. Again, this may not be true in reality, but knowing the exact time each evacuee left was not possible.

- 6. As explained previously, most people walk two to three abreast when in groups, even if the group contains more than two to three individuals (Costa 2010). This creates a crowd density of approximately three people per square meter, which is the most common density for urgent, purposeful walking in evacuations (Still 2014). To create this density while calculating travel time for each group of 142 evacuees, first, 142 was divided by three to determine the how many groups of three people abreast were in each of the 66 groups of 142 evacuees (i.e., 47.33 rounded to 48).
- 7. The model assumed that each of the 66 groups of three evacuees abreast from Step 6 left the stadium at one-second intervals. Thus, the minimum, mean, and maximum evacuation times for each group of 142 evacuees were calculated by adding the respective minimum, mean, and maximum travel time (Step 4) for minimum, mean, and maximum locomotion speeds (Step 2) to 47 (i.e., 48 groups of three evacuees abreast – 1; the first group of three evacuees required the minimum, mean, or maximum travel time from Step 4 to evacuate, and each subsequent group left at one-minute intervals afterward, so one minute for each subsequent group was added to the respective minimum, mean, or maximum travel times).

*Calculate Total Evacuation Time*. Total evacuation time is the time required for all of the evacuees to move from their stadium seats to a sidewalk or road network exit point. Thus, the evacuation time for evacuees who drove to the game was the sum of the travel times for the following segments: (1) stadium seats to stadium gates, (2) stadium gates (i.e., stadium centroid as described earlier in this chapter) to parking lot centroids, and (3) parking lot centroids to road network points. Similarly, the evacuation time for evacuees who walked to the game was the sum of the travel times for the following segments: (1) stadium seats to stadium gates and (2) stadium gates (i.e., stadium centroid as described earlier in this chapter) to sidewalk network exit points. Because the evacuees who drove to the game and the evacuees who walked evacuated simultaneously, the time required for all evacuees (i.e., those who drove and those who walked) to evacuate was the longer of the two. The specific equations used are in Table 7.

Table 7

*Total Evacuation Time Equations*



Table 7 (continued).



Table 7 (continued).












Although not done to facilitate immediate identification of the many variables, all of the aforementioned 36 equations can be written with the more mathematically traditional single-letter variable names. For example, in Equation 36 above, if *c* = maximum of the maximum evacuation time for walking evacuees using Zale (2010) locomotion speed,  $a =$  maximum of the maximum within-stadium evacuation time using Zale (2010) locomotion speed, and  $b =$  maximum of the maximum stadium centroid to sidewalk network exit points evacuation time using Zale (2010) locomotion speed, the equation to calculate the maximum of the maximum evacuation time for walking evacuees using Zale (2010) locomotion speed would be  $c = a + b$ .

Because evacuees who drove and those who walked to the stadium evacuated simultaneously, minimum, mean, and maximum total evacuation times for driving and walking evacuees at each locomotion speed condition (i.e., survey data and Zale (2010)) were compared. The greater of the two was the total evacuation time. For example, the minimum of the minimum total evacuation time for driving evacuees using the survey data was compared to minimum of the minimum total evacuation time for walking evacuees using the survey data. The longer time was the minimum total evacuation time using the survey data. This process was repeated to determine the mean and maximum total evacuation times using the survey data. Similarly, minimum total evacuation time for driving evacuees using the Zale (2010) data was compared to minimum total evacuation time for walking evacuees using the Zale (2010) data. The longer time was the minimum total evacuation time using the Zale (2010) data. This process was repeated to determine the mean and maximum total evacuation times using the Zale (2010) data.

Pedestrian Dynamics (2017) modeled evacuation only from stadium seats to stadium gates; it did not include evacuation outside the stadium. Thus, the evacuation time generated for the stadium seats to the stadium gates using the triangular distribution was not added to additional evacuation segments outside the stadium to generate total evacuation time.

## *Step 3: Validate and Assess the Accuracy of the Model and the Methodology*

Inferential statistics were used to compare the results of the within-stadium portion of the model under the three conditions. A Kolmogorov-Smirnov (K-S) Goodness-of-Fit Test revealed that the minimum, mean, and maximum evacuation times were not normal (i.e., *p* < 0.001 for each). Nevertheless, one-way ANOVA was used to compare the three locomotion speed conditions for the within-stadium evacuation, because: (1) this test is robust with respect to normality, particularly when the sample sizes are equal or very close to equal, as they are in this case, (2) parametric tests are more robust in general than nonparametric tests because they compare means rather than medians, and (3) the ANOVA nonparametric equivalent (i.e., Kruskal-Wallis ANOVA) produced the same results with respect to statistical significance (McGrew and Monroe 1993; Johnson 2015). Three ANOVAs were executed; the grouping variable for all of them was the locomotion speed condition and the dependent variables were the minimum, mean, and maximum evacuation times for each model run. An alpha level of 0.05, commonly used in human-related research except for medicine, was employed (Johnson 2015). A discussion of the findings of the inferential statistics is presented in the next chapter.

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### CHAPTER IV – RESULTS

This chapter presents the statistical analyses of the survey data and, based on the results of these analyses, identifies the variables that were used in the model. A discussion of these results, followed by the evacuation times (calculated per Chapter III), are also presented here. Finally, a discussion of inferential statistics used to assess accuracy of the computed evacuation times is presented. The questionnaire is in Appendix C.

## Statistical Analyses of Questionnaire Data

#### *Frequency Analyses*

Frequency analysis revealed that 165 participants (i.e., 48.2%) indicated they were male and 177 (i.e., 51.8%) stated they were female. One hundred and ninety participants (i.e., 54.0%) responded they were 18 to 25 years of age, 52 (i.e., 14.8%) indicated they were 26 to 35 years of age, 38 (i.e., 10.8%) stated they were 36 to 45 years of age, 41 (i.e., 11.6%) indicated they were 46 to 55 years of age, 16 (i.e., 4.5%) stated they were 56 to 65 years of age, and 15 (i.e., 4.3%) responded they were 66 years of age or older. Nine participants (i.e., 2.5%) indicated that the average size of their parties at football games was one, 44 participants (i.e., 12.2%) stated it was two, 46 participants (i.e., 12.7%) responded it was three, 64 participants (i.e., 17.7%) indicated it was four, and 198 participants (i.e., 54.8%) stated it was five or more.

Results of frequency analysis on the number of individuals less than eight years of age per party, the number of individuals between eight and 18 years of age per party, and the number of individuals per party requiring special accommodations are presented below in Tables 8, 9, and 10, respectively.

# Table 8



# *Number of Individuals Less than Eight Years of Age per Party*

## Table 9

## *Number of Individuals Eight to 18 Years of Age per Party*





# Table 10

# *Number of Individuals Requiring Special Accommodations per Party*



Twenty-six participants (i.e., 7.3%) responded that they usually attend one USM home football game per season, 31 participants (i.e., 8.7%) indicated that they usually attend two games, 47 participants (i.e., 13.1%) stated that they usually attend three games, 46 participants (i.e., 12.8%) responded that they tend to attend four games, 53 (i.e., 14.8%) and 155 (i.e., 43.3%) participants indicated that they attend five and six games per season, respectively.

One hundred and eighty-five survey respondents (i.e., 51.4%) indicated that they have been attending USM home football games for five years or less, 43 participants (i.e., 11.9%) indicated that they have been attending games for six to ten years, 35 participants (i.e., 9.7%) stated that they have been attending games for 10 to 15 years, 32 participants (i.e., 8.9%) responded that they have been attending games for 16 to 20 years, and 65 participants (i.e., 18.1%) indicated that they have been attending games more than 20 years. Two hundred seventy-four participants (i.e., 78.3%) stated that they generally spent time within the stadium during football games, while 76 (i.e., 21.7%) participants indicated that they tend to be outside the stadium during a game.

Frequency analysis of the questionnaire responses to the item addressing the number of people the participant traveled with to a game revealed that 24 participants (i.e., 6.7%) indicated that they usually traveled alone to football games, 30 participants (i.e., 8.4%) stated that they usually traveled with one other person, 77 participants (i.e., 21.5%) responded that they usually traveled with two other people, 51 participants (i.e., 14.2%) indicated that they usually traveled with three other people, 66 participants (i.e., 18.4%) stated that they usually traveled with four other people, 39 participants (i.e., 10.9%) responded that they usually traveled with five other people, 20 participants (i.e.,

5.6%) indicated that they usually traveled with six other people, five participants (i.e., 1.4%) stated that they usually traveled with seven other people, nine participants (i.e., 2.5%) responded that they usually traveled with eight other people, and 37 (i.e., 10.3%) participants indicated that they usually traveled with more than eight other people.

Two hundred and fifty-five survey participants (i.e., 71.8%) stated that they traveled to football games via car, truck, or van (i.e., a personal vehicle that was not a recreational vehicle or motor home), five participants (i.e., 1.4%) responded that they traveled via recreational vehicle or motor home, 91 participants (i.e., 25.6%) indicated that they walked, three participants (i.e., 0.8%) biked, and four participants (i.e., 0.3%) used other modes of transportation.

Two hundred and forty-two participants (i.e., 71.2%) stated that they did not have reserved parking spaces when attending football games, while 98 (i.e., 28.8%) responded that they did. Two hundred and twenty-seven participants (i.e., 63.2%) indicated that they traveled 20 miles or less to attend games, 28 participants (i.e., 7.8%) stated that they traveled 21 to 40 miles, 24 participants (i.e., 6.7%) responded that they traveled 41 to 60 miles, 21 participants (i.e., 5.8%) indicated that they traveled 61 to 80 miles, and 59 participants (i.e., 16.4%) stated that they traveled 81 miles or more.

One hundred and fifty-nine participants (i.e., 46.6%) responded that they did not usually consume alcoholic beverages while tailgating, while 182 participants (i.e., 53.4%) indicated that they did. Nine participants (i.e., 5.5%) stated that they usually consumed one alcoholic beverage while tailgating, 46 participants (i.e., 27.9%) responded that they usually consumed two, 22 participants (i.e., 13.3%) indicated that they usually consumed three, 21 participants (i.e., 12.7%) stated that they usually consumed four, 15 participants

(i.e., 9.1%) responded that they usually consumed five, 23 participants (i.e., 13.9%) indicated that they usually consumed six, three participants (i.e., 1.8%) stated that they usually consumed seven, nine participants (i.e., 5.5%%) responded that they usually consumed eight, two participants (i.e., 1.2%) indicated that they usually consumed nine, 11 participants (i.e., 6.7%) stated that they usually consumed 10, three participants (i.e., 1.8%) responded that they usually consumed 12, and one individual (i.e., 0.6%) indicated that he or she usually consumed 24.

The findings of frequency analysis of questionnaire responses to the item addressing time in which alcoholic beverages were consumed on game day revealed that nine participants (i.e., 4.9%) stated that they usually consumed alcoholic beverages over one hour on game day, 21 participants (i.e., 11.4%) responded that they usually consumed them over two hours, 28 participants (i.e., 15.1%) indicated that they usually consumed them over three hours, 45 participants (i.e., 24.3%) stated that they usually consumed them over four hours, 26 participants (i.e., 14.4%) responded that they usually consumed them over five hours, 31 participants (i.e., 16.8%) indicated that they usually consumed them over six hours, five participants (i.e., 2.7%) stated that they usually consumed them over seven hours, 12 participants (i.e., 6.5%) responded that they usually consumed them over eight hours, one participant (i.e., 0.5%) indicated that he or she usually consumed them over nine hours, two participants (i.e., 1.1%) stated that they usually consumed them over ten hours, one participant (i.e., 0.5%) responded that he or she usually consumed them over 11 hours, and four participants (i.e., 2.2%) indicated that they usually consumed them over more than 12 hours.

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With respect to a general feeling of safety while inside the M.M. Roberts Stadium during football games (i.e., the "USM Football Stadium Safety Questions" on the third page of the questionnaire – Appendix C) 15 participants (i.e., 4.2%) stated that they felt very unsafe, nine participants (i.e., 2.5%) responded that they felt somewhat unsafe, 33 participants (i.e., 9.3%) indicated that they felt neutral, 57 participants (i.e., 16.1%) stated that they felt somewhat safe, and 240 participants (i.e., 67.8%) responded that they felt very safe. With respect to a general feeling of safety while tailgating at a USM home football game, 12 participants (i.e., 3.4%) indicated that they felt very unsafe, eight participants (i.e., 2.3%) stated that they felt somewhat unsafe, 36 participants (i.e., 10.2%) responded that they felt neutral, 52 participants (i.e., 14.7%) indicated that they felt somewhat safe, and 246 participants (i.e., 69.5%) stated that they felt very safe.

The results in this paragraph are from the items in the "General Football Stadium Evacuation Questions" section on the third page of the questionnaire (Appendix C). Two hundred and eighty-five participants (i.e., 85.6%) responded that they had never evacuated from a large, outdoor public place, while 48 participants (i.e., 14.4%) indicated that they had. Of the participants who stated that they had evacuated from a large, outdoor public place, 26 participants (i.e., 61.9%) responded that these evacuations were due to thunderstorms, ten (i.e., 23.8%) were due to tornadoes, two (i.e., 4.8%) were due to bomb threats, and four (i.e., 9.5%) were due to other causes. Again of the participants who indicated that they had evacuated from a large, outdoor public place, six participants (i.e., 12.5%) stated that they did not immediately comply with any official evacuation orders, 41 participants (i.e., 85.4%) responded that they did immediately comply, and one participant (i.e., 2.1%) indicated that he or she was not officially ordered to evacuate. Of

the participants who indicated that they evacuated from a large, outdoor public place, 15 (i.e., 32.6%) stated that they left before the hazard event, 13 (i.e., 28.3%) responded that they left during, and 18 (i.e., 39.1%) indicated that they left after the event. Eight participants (i.e., 17.4%) stated that this event occurred less than one year ago, 24 participants (i.e., 52.2%) responded that it occurred one to five years ago, ten participants (i.e., 21.7%) indicated that it occurred six to ten years ago, two participants (i.e., 4.3%) stated that it occurred 11 to 15 years ago, and two participants (i.e., 4.3%) responded that it occurred more than 16 years ago.

The results in this paragraph are from the items in the "General Hazard History Questions" section on the third page of the questionnaire (Appendix C). One hundred and twenty-seven participants (i.e., 36.9%) indicated that they had never experienced a major hazard event in their lives, while 217 (i.e., 63.1%) stated that they had. Of the individuals who responded that they had experienced a hazard event in their lives, 149 participants (i.e., 79.7%) indicated that they experienced a hurricane, 23 participants (i.e., 12.3%) stated that they experienced a tornado, six participants (i.e., 3.2%) responded that they experienced a flood, four participants (i.e., 2.1%) indicated that they experienced an earthquake, one participant (i.e., 0.5%) stated that he or she experienced a large fire, two participants (i.e., 1.1%) responded that they experienced a bomb threat, and two participants (i.e., 1.1%) indicated that they experienced other types of hazards. Of the individuals who indicated that they had experienced a hazard event in their lives, ninetysix participants (i.e., 45.3%) stated that they did not evacuated during this hazard, while 116 (i.e., 54.7%) responded that they did. Continuing with the individuals who indicated that they had experienced a hazard event in their lives, twenty-eight participants (i.e.,

13.1%) stated that they did not immediately comply with any official evacuation orders, 108 participants (i.e., 50.7%) responded that they immediately complied, and 77 participants (i.e., 36.2%) indicated that they were not officially ordered to evacuate. Additionally, with this group, 14 participants (i.e., 6.8%) indicated that this hazard occurred less than one year ago, 51 participants (i.e., 24.9%) stated that this hazard occurred one to five years ago, 121 participants (59.0%) responded that this hazard occurred six to ten years ago, 14 participants (i.e., 6.8%) indicated that this hazard occurred 11 to 15 years ago, and five participants (i.e., 2.4%) stated that this hazard occurred 16 years ago or more.

Most of the participants responded that they sat in Sections E, F, K, L, M, and the Suites during games; the frequencies and percentages for the aforementioned sections, respectively, were 13 (i.e., 3.6%), 12 (i.e., 3.3%), 26, (i.e., 7.2%), 45 (i.e., 12.5%), 12 (i.e., 3.3%), and 10 (2.8%) (Figure 6).



*Figure 6.* M.M. Roberts Stadium seating chart (Southern Miss Athletics 2016).

Participants indicated that their heights ranged from 52.00 to 82.00 inches (*M* = 67.47 inches) and their weights ranged from 85.00 pounds to  $320.00 \, (M = 178.58)$ pounds). Calculated BMI ranged from 16.44 to 49.22 (*M* = 27.26). Calculated BAC ranged from 0.000032 to 0.041 (*M* = 0.0073).

*K-S Goodness-of-Fit Test*

The K-S Goodness-of-Fit Test was used to examine the normality of data obtained for each question, as well as for BAC and BMI (McGrew and Monroe 1993; Johnson 2015). Although the responses were not normal (Appendix F), both parametric tests and their nonparametric equivalents were used. Only the parametric results are

presented because parametric tests are more powerful than nonparametric due to the comparison of means rather than medians, all of the tests discussed in the remainder of this chapter were robust with respect to the assumption of normality, and there were no differences in significance between the parametric and nonparametric tests (McGrew and Monroe 1993; Johnson 2015). An alpha level of 0.05 was used for all inferential statistics (Johnson 2015).

## *One-Way ANOVA*

One-way ANOVA revealed a statistically significant relationship between age group (i.e., the independent variable) and BAC (i.e., the dependent variable),  $F(5, 114) =$ 2.362,  $p = 0.044$ . Tukey's posthoc test revealed that there were no statistically significant differences between age groups. Levene's test indicated that there was no homogeneity of variance  $(p = 0.019)$ , which was expected due to the absence of normality discussed in the previous paragraph. Although the ANOVA was statistically significant overall, these results were not included in the model because: (1) there were no statistically significant differences between age groups which could potentially have been used to alter the behavior of the representative agents, and (2) the effects of BAC on decision-making processes and behavior were minimal due to low BAC value (range 0.00003209 to 0.04094,  $M = 0.007302$ ), the presence of only six participants with BAC over 0.02 (i.e., when judgment usually begins to become impaired), and the absence of legally intoxicated participants (i.e,  $BAC = 0.08$  per Impaired (2006)).

#### Evacuation Model Implementation Outcomes

During the first segment of the evacuation, evacuees moved from stadium seats to stadium gates via three different locomotion speed conditions: (1) according to Table 6 in Chapter III, (2) a constant 1.5 meters per second, and (3) a triangular distribution with minimum, maximum, and mode speeds of 0.8 meters per second, 1.75 meters per second, and 1.35 meters per second, respectively. As discussed in Chapter III, the model was simulated multiple times for each speed condition. Tables 11 and 12 present simulated outputs for each locomotion speed. The raw data used in these calculations are in Appendix H.

Table 11

Condition	Minimum Number of Evacuees	Mean Number of Evacuees	Maximum Number of Evacuees	
	35,983	35,998.29	36,000	
$\mathcal{D}$	35,988	35,997.61	36,000	
3	35,983	35,997.00	36,000	

*Number of Evacuees Descriptive Statistics per Locomotion Speed Condition*

## Table 12

Condition	Number of Runs	Minimum <b>Evacuation Time</b> (s)		Mean Evacuation Time $(s)$		Maximum Evacuation Time (s)	
		Min	1.00	Min	419.00	Min	1,103.00
$\mathbf{1}$	28	Mean	1.36	Mean	420.96	Mean	1,137.50
		Max	2.00	Max	422.00	Max	1,249.00
$\overline{2}$	28	Min	1.00	Min	396.00	Min	1,025.00
		Mean	1.43	Mean	397.18	Mean	1,077.32
		Max	2.00	Max	399.00	Max	1,253.00
3	27	Min	1.00	Min	442.00	Min	1,135.00
		Mean	1.41	Mean	443.63	Mean	1,214.59
		Max	2.00	Max	445.00	Max	1,416.00

*Evacuation Time Descriptive Statistics per Locomotion Speed Condition*

The first component of the second segment of the evacuation determined the time required for all of the evacuees who drove to the game to move on foot from the stadium gates to their vehicles in parking lots, and then from their vehicles in parking lots to driving destination exit points. Locomotion speeds of 1.26 meters per second (i.e., survey data minimum), 1.46 meters per second (i.e., survey data mean), 1.51 meters per second (i.e., survey data maximum), and 1.5 meters per second (i.e., the speed used in Zale (2010)) were used to calculate the stadium gates (modeled as the stadium centroid as explained in Chapter III) to parking lots (modeled as parking lot centroids as explained in Chapter III) portion of this component time (Table 13). The raw data used in these calculations are in Appendix I. The minimum, mean, and maximum time required for evacuees to travel from parking lots to their driving destinations (i.e., road network exit points) were 674.59 seconds, 3,278.52 seconds, and 7,771.30 seconds, respectively. Table 13



*Stadium Gates to Parking Lots Evacuation Times*

The second component of the second segment of the evacuation determined the time required for all of the evacuees who walked to the game to move on foot from the stadium gates to the sidewalk network exit points. Locomotion speeds of 1.44 meters per second (i.e., survey data minimum), 1.47 meters per second (i.e., survey data mean), 1.51 meters per second (i.e., survey data maximum), and 1.5 meters per second (i.e., the speed used in Zale (2010)) were used to calculate the stadium gate to parking lot portion of this component time (Table 14).

Table 14



*Stadium Gates to Sidewalks Evacuation Times*

Tables 15 and 16 show the minimum, mean, and maximum total evacuation times using the survey locomotion speeds and a locomotion speed of 1.5 meters per second (Zale 2010) as calculated by Equations 1 through 36 in Table 7 (in Chapter III), as well as evacuation times for vacating the stadium using the default locomotion speed in the Pedestrian Dynamics model (Pedestrian Dynamics 2017). The values from Table 15 were converted into minutes to create Table 16 and graphed in Figures 7, 8, and 9 for ease of comprehension and comparison between input parameters.

# Table 15

# *Total Evacuation Time in Seconds*





## Table 16

## *Total Evacuation Time in Minutes*







*Figure 7.* Minimum total evacuation times graph.



*Figure 8.* Mean total evacuation times graph.





The survey locomotion speeds produced a longer minimum evacuation time for walking evacuees (17.81 minutes) than for driving evacuees (11.28 minutes), but longer mean and maximum evacuation times for driving evacuees (76.76 minutes and 165.01 minutes, respectively) than for walking evacuees (24.46 minutes and 37.80 minutes, respectively). The total evacuation time using the survey locomotion speed data was 165.01 minutes (i.e., the longest total evacuation time for driving and walking evacuees calculated with the survey data). The Zale (2010) locomotion speed produced longer minimum, mean, and maximum evacuation times for driving evacuees (15.11 minutes, 69.50 minutes, and 165.16 minutes, respectively) than for walking evacuees (2.91 minutes, 16.89 minutes, and 37.98 minutes, respectively). The total evacuation time using the Zale (2010) locomotion speed data was 165.16 minutes (i.e., the longest total evacuation time for driving and walking evacuees calculated with the Zale (2010) data).

The total evacuation time generated with the Zale (2010) data (i.e., 165.16 minutes) was very slightly greater than that generated by the survey data (i.e., 165.01 minutes). A comparison of within-stadium evacuation times was performed so that the Pedestrian Dynamics (2017) default locomotion speed could be included (Table 17; created by converting the values in Table 12 from seconds to minutes for easy comprehension). Table 17

Condition	Number of Runs	Minimum <b>Evacuation Time</b> (minutes)		Mean Evacuation Time (minutes)		Maximum <b>Evacuation Time</b> (minutes)	
		Min	0.017	Min	6.98	Min	18.38
1	28	Mean	0.023	Mean	7.02	Mean	18.96
		Max	0.033	Max	7.03	Max	20.82
$\mathcal{D}_{\mathcal{L}}$		Min	0.017	Min	6.60	Min	17.08
	28	Mean	0.024	Mean	6.62	Mean	17.95
		Max	0.033	Max	6.65	Max	20.88

*Within-Stadium Evacuation Times per Locomotion Speed Condition*



All three conditions produced nearly the same minimum evacuation times, although the mean of the minimum evacuation time for the first condition was 0.001 second shorter than that of the other two conditions. The minimum, mean, and maximum times of the mean evacuation time for the second condition were shorter than the respective values for the other two conditions, while the minimum, mean, and maximum times of the mean evacuation time for the third condition were longer than those for the other two. The minimum and mean of the maximum evacuation times for the second condition were the shortest of the respective values for the three conditions, while the maximum of the maximum was the shortest for the first condition. The minimum, mean, and maximum of the maximum were the longest for the third condition (Table 17).

Three one-way ANOVAs were used to compare within-stadium evacuation time in which the grouping variable was the locomotion speed condition and the dependent variables were the minimum, mean, and maximum evacuation times for each model run, N for the first, second, and third conditions was 28, 28, and 27, respectively. The

minimum and mean evacuation times had homogeneity of variance ( $p = 0.526$  and  $p =$ 0.383, respectively), while the maximum evacuation times did not ( $p = 0.032$ ). The ANOVA with the minimum times as the dependent variable was not statistically significant. The ANOVA with the mean times as the dependent variable was statistically significant,  $F(2, 80) = 22,243.02$ ,  $p < 0.001$ ), as was the ANOVA with the maximum times as the dependent variable,  $F(2, 80) = 36.62$ ,  $p < 0.001$ ). Tukey's posthoc tests revealed statistically significant differences for all of the pairwise comparison of groups for both of the statistically significant ANOVAs (Tables 18 and 19).

Table 18

Group 1	Group 2	Mean Difference*	value $\boldsymbol{p}$
Condition 1	Condition 2	23.79	< 0.001
Condition 1	Condition 3	$-22.67$	< 0.001
Condition 2	Condition 3	$-46.45$	< 0.001

*Mean Total Evacuation Time Statistically Significant Pairs*

\*Mean Difference = Group 1 Mean – Group 2 Mean

# Table 19



# *Maximum Total Evacuation Time Statistically Significant Pairs*

Mean Difference = Group 1 Mean – Group 2 Mean

### CHAPTER V – DISCUSSION AND CONCLUSIONS

This chapter discusses the results presented in Chapter IV, identifies the limitations and error sources of this project, and explains possible applications of the model and future avenues of research. The conclusions derived from the findings are also presented in this chapter.

## Discussion of Research Findings

Because the goal of this project was to determine the time required for all evacuees to exit the stadium and campus, the maximum total evacuation times for each segment of the model were determined. All of the evacuees exiting the stadium and campus in any of the minimum evacuation times for any of the conditions is physically impossible, as they range from 0.017 minutes to 20.54 minutes. While the mean evacuation times provide a useful measure of central tendency, and evacuees do exit within this time, these times do not account for an evacuation of a full stadium. Thus, of maximum evacuation times are of particular interest, as all of the evacuees would be able to evacuate the entire impact zone.

The total evacuation times (i.e., the time required for all of the evacuees to move from their seats in the stadium to a road or sidewalk network exit point) generated by the survey data and the Zale (2010) locomotion speed data (i.e., a locomotion speed of 1.5 meters per second) were 165.01 minutes and 165.16 minutes, respectively. Thus, the total evacuation time in both studies was approximately 2.75 hours with a difference of only 8.82 seconds. The longest within-stadium evacuation time for any of the three conditions in this research was 1,416.00 seconds (i.e., 23.6 minutes; the maximum of the maximum time for the third condition; from Table 11 in Chapter IV).

Comparison of the evacuation times generated by the three conditions for the within-stadium portion of the evacuation model in this project (i.e., Table 12 in Chapter IV) revealed that the minimums and maximums of the minimums were the same for all three conditions. The means of the minimum varied; however, since the minimums and maximums of the minimums were 1.00 seconds and 2.00 seconds, the values were very close. The second condition produced the shortest minimum, mean, and maximum of both the mean and the maximum evacuation times, while the third condition produced the longest. In addition to being visibly apparent, these differences were reflected in the oneway ANOVAs; the ANOVA for the minimum times was not statistically significant, while the ANOVAs for the mean and maximum times were statistically significant. As mentioned earlier in this section, maximum evacuation time is especially important because it is the time required for all of the evacuees to evacuate. The maximum evacuation times for conditions 1, 2, and 3 were 1,249.00 seconds (i.e., 20.82 minutes), 1,253.00 seconds (i.e., 20.88 minutes), and 1,416.00 seconds (i.e., 23.60 minutes), respectively (i.e., from Table 12 in Chapter IV). Using locomotion speed determined by the survey responses (i.e., Condition 1) resulted in the shortest maximum evacuation time, while the default locomotion speed for the Pedestrian Dynamics (2017) software (i.e., a triangular distribution with minimum, mode, and maximum locomotion speeds of 0.8, 1.35, and 1.75 meters per second, respectively) resulted in the longest maximum evacuation time. These changes in maximum evacuation time derived from locomotion speed condition, and the fact that the maximum evacuation time based on the first condition (i.e., the survey data in Table 17) was lower than that from the other two conditions (i.e., constant locomotion speed of 1.5 meters per second and the

aforementioned triangular distribution), indicate that using location-specific locomotion speed data influences the time required for all evacuees to exit and thus should be included if possible when creating an evacuation model for a specific venue. Ideally, the evacuation times generated by each of the conditions should be examined for accuracy against evacuation time from an actual evacuation of the stadium; however, currently that data does not exist.

The total evacuation time computed in this research was 2.75 hours when using both the survey data and a locomotion speed of 1.5 meters per second, as mentioned earlier in this section). This time was between the mean and the maximum total evacuation times (i.e., 2.1 hours and 4.1 hours, respectively) calculated in Zale (2010), which also used a locomotion speed of 1.5 meters per second. As explained in Chapter III, this research used an agent-based model to compute evacuation time within the stadium and a flow-based model to estimate evacuation time outside the stadium. In this project, an attempt was made to accurately depict evacuee movement and crowd density outside the stadium (i.e., in more open space than within the stadium) by modeling evacuee movement using groups of three as explained in Chapter III, rather than by assuming that evacuees moved in a single file line, as in Zale (2010).

The longest within-stadium evacuation time calculated in this research was 23.6 minutes (i.e., the maximum of the maximum time generated by the triangular distribution of locomotion speed, as mentioned earlier in this section). This estimated time was shorter than the mean (i.e., 41.9 minutes) and maximum (i.e., 50.8 minutes) evacuation times computed for the stadium using the flow-based evacuation model in Zale (2010), in which all evacuees moved single file at a locomotion speed of 1.5 meters per second.

This is likely due to the differences in modeling approaches (i.e., flow-bases versus agent-based, as discussed in Chapter II) and how the stadium itself was modeled. In Zale (2010), the stadium was modeled in two dimensions using a raster layer in ArcMap. Obviously, the stadium is three-dimensional, and modeling in two dimensions introduced the following errors: (1) the upper deck ramps were not included, which meant all evacuees had to exit via the stand aisles (which in reality is impossible due to the stadium's construction); (2) the vormitories (i.e., entrances to the stadium stands that pierce the bank of the stands (Merriam-Webster 2017)) were not included, which meant that all evacuees had to exit via the field-level gates (also impossible in reality due to the stadium construction); and (3) the distance from the top of the stands to the bottom was measured in two dimensions rather than in three, so the change in elevation, which would increase the distance, was not included. In this research, architectural plans of the stadium in computer automated drafting format and scans of hand drawings were used to create a three-dimensional stadium model, thus eliminating the aforementioned errors and greatly increasing the accuracy of the evacuation routes and stadium exit locations. Furthermore, instead of moving in single-file lines along evacuation routes to exits (as in Zale 2010), evacuees in this project were modeled to move naturally, ebbing and flowing in groups and then in a single-file in narrow exit corridors (i.e., when exiting seat rows and stand corridors, but not after passing through vormitories).

## Error Sources

Despite its increased accuracy, this project contained the following sources of error: (1) potential questionnaire data inaccuracy, (2) locations and actions of evacuees when the evacuation order was given, (3) BAC input parameters, (4) using BMI to

estimate physical fitness, (5) questionnaire versus Census age categories, (6) use of nested Bernoulli functions to assign within-stadium locomotion speeds, (7) the model of the physical structure of the stadium, and (8) the methodology used to model evacuation outside the stadium.

Survey participants could have accidentally or intentionally provided inaccurate information on the questionnaire. Although the questionnaire was reviewed by experts during its development and administration, participants may have misunderstood what an item(s) was asking. On the other hand, they may have understood the meaning of an item, but chose not to provide the correct response. The only way to eliminate error related to self-reported measures is by direct observation of participant behavior by the researcher (Johnson 2015), which was not possible for many items on the questionnaire (e.g., Do they have any past experience with hazard events?). Thus, despite the potential error, using a questionnaire to gather participant data was the most feasible method.

The model assumed that: (1) all of the evacuees were in their seats when the order to evacuate was given and (2) all of the evacuees immediately heard and complied with the evacuation order. In reality, evacuees may not be in their seats; they could potentially be in other areas of the stadium, such as concessions stands, restrooms, or corridors. They also may not immediately hear, comprehend, and/or comply with the evacuation order. However, as there was no way to determine the location of each evacuee at the beginning of the simulation, the model assumed that the evacuees were in their seats in the stadium.

Although the equation used to calculate BAC accounted for many factors contributing to it (i.e., gender, number of drinks consumed, quantity of alcohol in each drink consumed, and time period over which the drinks were consumed), it did not
account for all of them (e.g., tolerance to alcohol or the consumption of food or medications with the alcoholic beverages), thereby introducing error (Alha 1951; Widmark 1981; Gullberg 1994). Since an equation that includes all possible factors when calculating BAC did not exist, correcting this error was not possible (Gullberg 1994). Additionally, this study assumed that the quantity of alcohol for each drink was a constant 5% (i.e., the average quantity of alcohol in 12 ounces of beer), when in reality this may not be true; depending on the type and volume of the beverage, the quantity of alcohol could be higher or lower (NIAA n.d.). However, the constant of 5% was used because (1) beer in 12-ounce quantities was the most common alcoholic beverage consumed at football games, (2) this study was interested in the average alcohol consumption per participant, and (3) consuming alcoholic beverages by tailgaters on the campus is illegal, which prohibited collection specific data about beverage choice and quantity (NIAA n.d.).

Although BMI is often used as a proxy of physical fitness, it is not an accurate substitute (About BMI 2014). In general, individuals with lower BMIs are more physically fit than individuals with higher BMIs (About BMI 2014). However, the equation used to calculate BMI included only height and weight as input parameters, which are not the only indicators of physical fitness (About BMI 2014). Other indicators, such as body fat percent, muscle mass weight, and resting and maximum volume of oxygen consumed by the body per minute, were not included in the BMI equation (About BMI 2014). Thus, a person with a relatively high BMI (i.e., classified as overweight or obese) could potentially be more physically fit than a person with a low or average BMI (i.e., classified as underweight or normal weight) if the person with the higher BMI had

more muscle mass and lower body fat percentage than the person with the lower BMI. However, as an equation creating an index for general fitness that included height, weight, and body composition did not exist, BMI was used (About BMI 2014).

The participants were classified according to the U.S. Census Bureau's categories, although the age categories used to determine locomotion speed were 60 years or less (i.e., younger) and greater than 60 years (i.e., older) (Carey 2005). Thus, individuals aged 56 through 60 years were categorized differently depending on the classification scheme used. These individuals were placed in the older age group when determining locomotion speed to minimize this error because: (1) older people tend to walk more slowly than younger people (Carter 2005), (2) to err on the side of safety and overestimate rather than underestimate when determining evacuation time, and (3) only nine survey participants (i.e., 2.49%) indicated that their ages were 56 through 60 years.

Although the nested Bernoulli function was used to model locomotion speeds, the model did not account for accurate distribution of locomotion speeds among agents due to lack of data. However, in some instances agents may potentially be grouped by age and/or gender (i.e., individuals sitting in the student section would likely be assigned the younger male or younger female locomotion speeds), which the model did not reflect.

That architectural drawings of the ramp and upper deck on the east side of the stadium used to create the model were hand-drawn. Therefore, these files could not be converted into a format that the modeling software could use (i.e., computer-automated drafting files). To resolve this, a mirror image of the ramp and upper deck on the west side of the stadium was created to use on the east side. While the mirror image closely approximates the size, shape, spatial orientation, and location of the actual east side upper deck and ramp, it was not made digital architectural drawings of the east side structures and may contain errors.

The model assumed that evacuees moved on foot from the stadium centroid to parking lot centroids or sidewalk network exit points. In reality, they moved from the stadium gates to parking spaces or anywhere along the perimeter of the campus. Due to the inavailability of data for football game attendees who parked off campus (i.e., in nearby shopping center parking lots), in this model, all evacuees parked on campus; however, they could have parked either on or off campus (i.e., in parking lots of nearby shopping centers and apartment complexes). Another assumption is that evacuees drove from parking lots to road network exit points along routes using the fastest travel times while moving at the prescribed speed limits. In reality, evacuees may not choose the route with the shortest travel time (or even be aware of all of the available routes), and traveling at the speed limit may be difficult due to potential traffic jams when all of the evacuating vehicles attempt to simultaneously exit the campus, thus increasing evacuation time. The model also evenly distributed the evacuees who drove to the game among all of the parking lots. However, the number of spaces per parking lot varies, which means evacuees could never be evenly divided among them. Similarly, evacuees who walked to the game were homogenously distributed among sidewalk network exit points and routed to them along a straight-line distance. Like evacuees who drove to the game, these evacuees would most likely not be evenly divided among the sidewalk network points and may or may not move in straight-line distances to the edge of campus. They also may or may not move in groups of three abreast, and likely will not move in groups of three abreast linearly, as the model depicted.

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#### Limitations

The first limitation of this research was that secondary data used to determine locomotion and driving speeds of evacuees. If this was collected at the time of the survey administration, locomotion and driving speeds of potential evacuees could be used in the model.

Two additional complimentary limitations were that the model was not based on a specific hazard event and the assumption that all evacuation routes were available. Examining total evacuation time and evacuee movement and route choice when the evacuation routes were impeded by the hazard itself (e.g., a fire, explosion, or chemical plume) and/or when roads and stadium corridors and exits are blocked, structurally unsound, or otherwise inaccessible would help stadium and emergency managers and staff plan for evacuations requiring addition effort and resources.

#### Model Applications

Stadium and emergency managers and staff could use this model prior to football games to aid in their emergency response training drills. The methodology used in this model can be adapted to other sports stadia, as well as other venues of mass gathering, such as amusements parks, concert halls, and shopping malls. Similarly, the questionnaire can be adapted to gather evacuee attribute data for inclusion in such evacuation models. Finally, this research complements the Pedestrian Dynamics software and extends its functionality by incorporating survey-based audience characteristics in evacuation time assessment.

#### Future Research

One area of future research is to collect locomotion speeds of potential evacuees, rather than determining it based on age and gender. This model used locomotion speeds from secondary sources and probability distributions, which, while likely produced a more accurate total evacuation time than the flow-based model in Zale (2010), may or may not accurately depict the total evacuation time of the M.M. Roberts Stadium.

Another avenue of research is to model evacuation due to a specific hazard event (e.g., fire, tornado, explosion, thunderstorm) and include impacts of the event itself in the model (e.g., stadium exit or road/sidewalk closures due to an explosion). By doing this, stadium and emergency managers and staff can examine how hazard events most likely to occur would affect evacuation routes and subsequent evacuation time, and adjust emergency response plans accordingly to ensure the fastest possible evacuation, thus ensuring safety of evacuees.

Finally, the pedestrian evacuation outside the stadium and the vehicular evacuation could be agent-based, thus truly combining pedestrian and vehicle evacuation into one agent-based modeling software package. Evacuation of a stadium (or other venue of mass gathering) often does not end at the stadium gates (e.g., if the game will not continue following the hazard event); evacuees must also leave the surrounding area. Thus, the ability to model all phases of the evacuation (i.e., from leaving stadium seats to exiting the surrounding area) with one software package would make its use by venue and emergency managers and staff easier, and estimate evacuation time more accurately.



National Center for Spectator Sports Safety and Security (NCS<sup>4</sup>)

118 College Drive #5193 | Hattiesburg, MS 39406-0001 Phone: 601.266.6183 | Fax: 601.266.6125 | www.ncs4.com

January 23, 2015

To Whom It May Concern:

I am writing this letter in support of the proposal "Optimizing Stadium Evacuation by Integrating Geo-computation and Affordance Theory". This proposal will be submitted for a Doctoral Dissertation Research Initiative (DDRI) grant funded by the National Science Foundation.

Our National Center for Spectator Sports Safety and Security is willing to collaborate with the researchers and to assist in their research activities. Specifically, we will be assisting with the survey administration logistics with the University of Southern Mississippi Athletic Department and with the development of a stadium model.

We consider this proposed research to be very important in creating new approaches in assisting stadium first responders with their evacuation planning. It is the hope that this research will identify a more efficient and effective process to plan for stadium evacuations.

Sincerely,

Lou Marciani, Ed.D. Director

## THE UNIVERSITY OF SOUTHERN MISSISSIPPI. **INSTITUTIONAL REVIEW BOARD** 118 College Drive #5147 | Hattiesburg, MS 39406-0001 Phone: 601.266.5997 | Fax: 601.266.4377 | www.usm.edu/research/institutional.review.board **NOTICE OF COMMITTEE ACTION** The project has been reviewed by The University of Southern Mississippi Institutional Review Board in accordance with Federal Drug Administration regulations (21 CFR 26, 111). Department of Health and Human Services (45 CFR Part 46), and university guidelines to ensure adherence to the following criteria:  $\bullet$ The risks to subjects are minimized. The risks to subjects are reasonable in relation to the anticipated benefits.  $\bullet$ The selection of subjects is equitable.  $\bullet$ Informed consent is adequate and appropriately documented. Where appropriate, the research plan makes adequate provisions for monitoring the data collected to ensure the safety of the subjects. Where appropriate, there are adequate provisions to protect the privacy of subjects and to maintain the confidentiality of all data. Appropriate additional safeguards have been included to protect vulnerable subjects. Any unanticipated, serious, or continuing problems encountered regarding risks to subjects must be reported immediately, but not later than 10 days following the event. This should be reported to the IRB Office via the "Adverse Effect Report Form". If approved, the maximum period of approval is limited to twelve months. Projects that exceed this period must submit an application for renewal or continuation. PROTOCOL NUMBER: 15043001 PROJECT TITLE: Optimizing Stadium Evacuation by Integrating Geo-computation and Affordance Theory PROJECT TYPE: New Project RESEARCHER(S): Joslyn Zale COLLEGE/DIVISION: College of Science and Technology DEPARTMENT: Geography and Geology FUNDING AGENCY/SPONSOR: N/A IRB COMMITTEE ACTION: Expedited Review Approval PERIOD OF APPROVAL: 05/01/2015 to 04/30/2016 Lawrence A. Hosman, Ph.D. **Institutional Review Board**

### APPENDIX B Institutional Review Board Approval Letter

### APPENDIX C USM Football Game Attendee and Tailgater Questionnaire







### APPENDIX D BAC Calculations

USM's Ticket Office revealed that the most common beverage consumed while tailgating was beer in approximately 12-fluid-ounce increments. According to the National Institute on Alcohol Abuse and Alcoholism, beer contains about 5% alcohol (NIAA n.d.). Thus, each 12-fluid-ounce quantity of beer contains 0.60 fluid ounces of alcohol (i.e., 12 fluid ounces of beer \* 0.05 alcohol).

Widmark's equation is used by forensic scientists and breathalyzers to compute BAC (Alha 1951; Widmark 1981; Gullberg 1994). Thus, in this research, it was used to compute the BAC of individuals attending football games at the M.M. Roberts Stadium. Widmark's equation is as follows:

$$
Ct = [(0.8 * A * f) / (P * 16 \text{ ounces per pound})] - \text{Bt}
$$

where:

 $t =$  time in which the number of alcoholic beverages (i.e., A) were consumed in hours

 $C_t = BAC$  in g/100 mL at time t

 $A =$  number of alcoholic beverages consumed in time t

 $f =$  number of fluid ounces of alcohol per unit A above (a constant value

of 0.60; derived in the first paragraph of this appendix)

 $P =$  body weight in pounds

- $\beta$  = drop in blood concentration per hour (a constant value of 0.015
	- kg/L/hr)

Values for t, A, and P were obtained from items on the questionnaire.  $C_t$  was calculated for each participant who provided t, A, and  $P (N = 120)$ .

### APPENDIX E BMI Calculations

According to the CDC, BMI is the most widely used, but admittedly imperfect,

quantitative estimate of physical fitness and is calculated as follows (About 2014):

 $BMI = (w / h^2) * 703$ 

where:

BMI = body mass index (a unit-less value)

 $w = weight$  in pounds

 $h = height$  in inches

Values for w and h were obtained from items on the questionnaire. BMI was calculated for each participant who provided w and h ( $N = 327$ ).

# APPENDIX F Kolmogorov-Smirnoff Goodness-of-Fit Test Results

## Table A1.



# *Kolmogorov-Smirnoff Goodness-of-Fit Test Results*

Table A1 (continued).



Table A1 (continued).



### APPENDIX G Linear Regression Results

Based on the findings of Carey (2005), which examined the effects of age group and gender on walking speed at inner city crosswalks, linear regression was used to examine the relationship between walking speed (i.e., the dependent variable) and gender and age group (i.e., predictive variables). Gender and age group explained a statistically significantly proportion of variance in walking speed,  $R^2 = 0.70$ ,  $F(2, 337) = 384.19$ ,  $p <$ 0.001. Both gender ( $\beta$  = -0.65,  $t(337)$  = -21.57,  $p < 0.001$ ) and age group ( $\beta$  = -0.54,  $t(337) = -18.05$ ,  $p < 0.001$ ) statistically significantly predicted walking speed.

Both BMI and BAC are partially determined by an individual's weight (Appendices D and E) (About 2014; Alha 1951; Widmark 1981; Gullberg 1994). Furthermore, frequency analysis of the questionnaire data, presented in Chapter IV, revealed that the most commonly consumed number of alcoholic beverages was two (27.9% of participants); the most common window of alcohol consumption was four hours (24.3% of participants); and BAC ranged from 0.00003209 to 0.04094 with a mean of 0.007302, only six participants over 0.02 (i.e., at which there may be some judgment impairment), and no participants over the legal limit of intoxication (i.e.,0.08) (Impaired 2016); thus, the effects of alcohol consumption on the decision-making processes and behavior of evacuees were most likely minimal.

While Carey (2005) did not include BMI or BAC, all participants in that study must presumably have had BMI and BAC values, even if the BAC values were extremely close to zero, and thus similar, but not the same, as those of the survey participants for this research. Therefore, in a final attempt to include BMI and BAC in this project, three unorthodox linear regressions were used to try to examine the relationship between

gender, age group, BMI, BAC, and locomotion speed, keeping in mind that the independent variables came from the questionnaire data for this project and the walking speed came from Carey (2005), and the results from these analyses may not be viable due to this combination of data sets.

In the first linear regression, the independent variables were gender, age group, BMI, and BAC, and the dependent variable was locomotion speed. Although this model was statistically significant overall  $(R^2 = 0.70, F(4, 115) = 67.44, p < 0.001$ , the only statistically significant predictors were gender  $(β = -0.72, t(115) = -13.16, p < 0.001)$  and age group ( $\beta$  = -0.46,  $t(115)$  = -8.57,  $p < 0.001$ ).

Since BMI and BAC were not statistically significant predictors of locomotion speed, their relationship to locomotion speed was examined in a second linear regression in which gender and age group were the independent variables, BMI and BAC were covariates, and locomotion speed was the dependent variable. Like the previous model in which BMI and BAC were independent variables rather than covariates, this model was statistically significant overall  $(R^2 = 0.70, F(4, 115) = 67.44, p < 0.001$ , but the only statistically significant predictors were gender  $(β = -0.72, t(115) = -13.16, p < 0.001)$  and age group ( $\beta$  = -0.46,  $t(115)$  = -8.57,  $p < 0.001$ ).

Finally, a third linear regression in which gender and age group were the independent variables, BMI and BAC were moderators, and locomotion speed was the dependent variable was conducted in a final attempt to examine the relationship between the variables. Similar to the previous results, overall, the model was statistically significant  $(R^2 = 0.71, F(6, 113) = 44.93, p < 0.001)$ . However, only gender was a statistically significant predictor  $(β = -0.77, t(113) = -4.77, p < 0.001)$ .

Since gender and age group were statistically significant predictors when BMI and BAC were not included as covariates or moderators, research examining the collective effects of gender, age, BMI, and BAC on walking speed was not present, and Carey (2005) examined the effects of gender and age group on locomotion speed at inner city crosswalks, which is usually fast and purpose-filled movement (i.e., similar to evacuation), only gender and age group were used to determine locomotion speed in this model.

Table A2.

*Within-Stadium Evacuation Times for Condition #1*

Run	Number of Evacuees	Minimum <b>Evacuation Time</b> (s)	Mean <b>Evacuation Time</b> (s)	Maximum Evacuation Time(s)
$\,1\,$	36000	$\,1\,$	421	1109
$\mathbf{2}$	35998	$\,1\,$	422	1130
$\mathfrak{Z}$	36000	$\mathbf{1}$	422	1245
$4*$	35976	$\mathbf{2}$	422	1107
$5**$	35999	$\mathbf{1}$	443	1389
$6***$	35989	$\sqrt{2}$	421	1349
$7*$	35837	$\mathbf{1}$	418	1104
$8*$	35776	$\mathbf{1}$	418	1124
$\mathbf{9}$	36000	$\mathbf 1$	421	1111
10	36000	$\mathbf{2}$	420	1184
11	36000	$\mathbf 1$	421	1117

Table A2 (continued).



Table A2 (continued).



## Table A2 (continued).



\*Run not used in calculations because the simulated number of evacuees was was 35,979 or less (i.e., more than 20 less than 36,000).

\*\*Run not used in calculations because the maximum evacuation time was more than 90 seconds greater than the largest cluster of evacuation times.

### Table A3.

## *Within-Stadium Evacuation Times for Condition #2*



Table A3 (continued).



Table A3 (continued).



# Table A3 (continued).



\*Run not used in calculations because the simulated number of evacuees was 35,979 or less (i.e., more than 20 less than 36,000).

### Table A4.

## *Within-Stadium Evacuation Times for Condition #3*



Table A4 (continued).



Table A4 (continued).



\*Run not used in calculations because the simulated number of evacuees was 35,979 or less (i.e., more than 20 less than 36,000).

APPENDIX I Stadium Centroid to Parking Lot Centroid Raw Data and Intermediate

Results

The data and intermediate results are listed using each step from Chapter III.

Step 1: The distance between the centroid of the stadium and that of each parking lot (i.e., 56 distances) was measured using the Near tool in ArcGIS (Figure A1 and the NEAR\_DIST field of Table A5, both in Appendix I).



Figure A1. Stadium centroid to parking lot centroid near features.

# Table A5.

*Stadium Centroid to Parking Lot Centroid Near Analysis Data Results*

<b>FID</b>	ORIG_NEAR_ <b>FID</b>	NEAR_ <b>DIST</b>	t_s_1_26		$t_s$ $1_46$ $t_s$ $1_51$ $t_s$ $1_5$	
$\overline{0}$	$\overline{0}$	363.585712		288.56009 249.03131	240.78524	242.39048
$\mathbf{1}$	$\overline{0}$	527.201787	418.41412	361.09711	349.14026	351.46786
$\overline{2}$	$\boldsymbol{0}$	577.623302		458.43119 395.63240	382.53199	385.08220
3	$\overline{0}$	1091.05007		865.91276 747.29457	722.54972	727.36671
$\overline{4}$	$\theta$	592.476003	470.21905	405.80548	392.36821	394.98400
5	$\overline{0}$	557.573368	442.51855	381.89957	369.25389	371.71558
6	$\overline{0}$	656.013796	520.64587	449.32452	434.44622	437.34253
7	$\overline{0}$	642.816548		510.17186 440.28531	425.70632	428.54437
8	$\overline{0}$	747.859092	593.53896	512.23225	495.27092	498.57273
9	$\boldsymbol{0}$	868.282966	689.11347	594.71436	575.02183	578.85531
10	$\overline{0}$	977.248378		775.59395 669.34820	647.18436	651.49892
11	$\boldsymbol{0}$	602.212945			477.94678 412.47462 398.81652	401.47530

Table A5 (continued).

<b>FID</b>	ORIG_NEAR_ <b>FID</b>	<b>NEAR</b> <b>DIST</b>	$t_{S_1}$ $-26$	t_s_1_46	$t_s$ _1 _51	t_s_1_5
12	$\theta$	824.903814	654.68557	565.00261	546.29392	549.93588
13	$\theta$	649.686999	515.62460	444.99109	430.25629	433.12467
14	$\theta$	807.752998	641.07381	553.25548	534.93576	538.50200
15	$\overline{0}$	938.670125	744.97629	642.92474	621.63584	625.78008
16	$\theta$	705.472277	559.89863	483.20019	467.20018	470.31485
17	$\theta$	440.362105	349.49373	301.61788	291.63053	293.57474
18	$\theta$	387.637256	307.64862	265.50497	256.71341	258.42484
19	$\theta$	368.310138	292.30963	252.26722	243.91400	245.54009
20	$\theta$	372.780556	295.85758	255.32915	246.87454	248.52037
21	$\theta$	422.003333	334.92328	289.04338	279.47241	281.33556
22	$\overline{0}$	353.015604		280.17111 241.79151	233.78517	235.34374
23	$\theta$	477.373322		378.86772 326.96803	316.14127	318.24888
24	$\overline{0}$	748.364923		593.94041 512.57871	495.60591	498.90995

Table A5 (continued).

ORIG <b>FID</b>	NEAR <b>FID</b>	NEAR <b>DIST</b>	$t_s_1_2_6$		$t_s$ 1 46 $t_s$ 1 51	t_s_1_5
25	$\theta$	582.358374	462.18919	398.87560	385.66780	388.23892
26	$\theta$	515.637862	409.23640	353.17662	341.48203	343.75857
27	$\overline{0}$	673.489965	534.51584	461.29450	446.01984	448.99331
28	$\overline{0}$	154.880425	122.92097	106.08248	102.56982	103.25362
29	$\theta$	192.406893	152.70388	131.78554	127.42178	128.27126
30	$\boldsymbol{0}$	272.046221	215.90970	186.33303	180.16306	181.36415
31	$\theta$	155.801810	123.65223	106.71357	103.18001	103.86787
32	$\overline{0}$	265.696519	210.87025	181.98392	175.95796	177.13101
33	$\theta$	409.612785	325.08951	280.55670	271.26674	273.07519
34	$\theta$	225.601906	179.04913	154.52185	149.40524	150.40127
35	$\theta$	438.037619 347.64890 300.02577			290.09114	292.02508
36	$\theta$	305.805678		242.70292 209.45594	202.52032	203.87045
37	$\boldsymbol{0}$	523.357676		415.36323 358.46416 346.59449		348.90512

Table A5 (continued).

ORIG <b>FID</b>	NEAR_ <b>FID</b>	NEAR <b>DIST</b>	$t_s_1_2_6$	t_s_1_46	t_s_1_51	t_s_1_5
38	$\overline{0}$	674.996153	535.71123	462.32613	447.01732	449.99744
39	$\overline{0}$	471.343016	374.08176	322.83768	312.14769	314.22868
40	$\boldsymbol{0}$	181.268778	143.86411	124.15670	120.04555	120.84585
41	$\theta$	691.949895	549.16658	473.93828	458.24496	461.29993
42	$\theta$	274.674646	217.99575	188.13332	181.90374	183.11643
43	$\overline{0}$	766.744043	608.52702	525.16715	507.77751	511.16270
44	$\theta$	528.935318	419.78993	362.28446	350.28829	352.62355
45	$\theta$	764.731423	606.92970	523.78865	506.44465	509.82095
46	$\theta$	517.816846	410.96575	354.66907	342.92506	345.21123
47	$\theta$	410.775035	326.01193	281.35276	272.03645	273.85002
48	$\overline{0}$	428.394852		339.99591 293.42113	283.70520	285.59657
49	$\overline{0}$	357.802466	283.97021	245.07018	236.95528	238.53498
50	$\overline{0}$	215.545957 171.06822 147.63422 142.74567				143.69730

Table A5 (continued).

ORIG_ <b>FID</b>	NEAR <b>FID</b>	NEAR_ <b>DIST</b>	t s $1\,26$	t s $1\,46$	t s $1\,51$	t_s_1_5
51	$\overline{0}$	107.743609	85.51080	73.79699	71.35338	71.82907
52	$\overline{0}$	438.163535	347.74884	300.11201	290.17453	292.10902
53	$\overline{0}$	375.141821	297.73160	256.94645	248.43829	250.09455
54	$\overline{0}$	239.036410	189.71151	163.72363	158.30232	159.35767
55	$\theta$	264.411401	209.85032	181.10370	175.10689	176.27427

Table A5 field definitions:

ORIG\_FID: The feature identification number of each parking lot centroid, locations shown in Figure 7.

NEAR\_FID: The feature identification number of the stadium centroid, location shown in Figure 7.

NEAR\_DIST: the straight-line distance between the NEAR\_FID and each ORIG\_FID in meters.

t\_s\_1\_26: The time in seconds to travel each distance with a locomotion speed of 1.26 meters per second.

t\_s\_1\_46: The time in seconds to travel each distance with a locomotion speed of 1.46 meters per second.

t\_s\_1\_51: The time in seconds to travel each distance with a locomotion speed of 1.51 meters per second.

t\_s\_1\_5: The time in seconds to travel each distance with a locomotion speed of 1.5 meters per second.

Step 2: Minimum, mean, and maximum locomotion speeds for survey participants who indicated that they drove to games (i.e., car/truck/van or RV/motor home responses to questionnaire Item 9) were calculated.

Step 3: The minimum, mean, and maximum travel times for each of the 56 stadium centroid to parking lot centroid distances (i.e., Step 1 results) were calculated by dividing each distance by the minimum, maximum, and average locomotion speeds from Step 2, as well as a locomotion speed of 1.5 meters per second (e.g., minimum travel time for distance  $#1 =$  distance  $#1 /$  minimum locomotion speed). See Table A5 (Appendix I), fields t\_s\_1\_26, t\_s\_1\_46, t\_s\_1\_51, and t\_s\_1\_5, above for these results.

Step 4: The minimum, mean, and maximum travel times for this component (i.e., all of the stadium centroid to parking lot centroid distances) were calculated from the results of Step 3 (ie., minimum, mean, and maximum travel times based on all of the distances for each speed) (Table A5, Appendix I).

Table A6.

*Minimum, Mean, and Maximum Travel Times for Locomotion Speeds of Driving* 

*Evacuees*



Step 5: The number of driving evacuees (i.e., 26,644) was divided by the number of parking lots (i.e., 56) to determine the number of evacuees per lot (i.e., 475.79 evacuees rounded to 476, as fractional numbers of people are not possible). Although this number was likely, not true in reality, there was no way to know how many evacuees parked in each lot, so the evacuees were evenly distributed among all of the lots. The

model assumed that each group of 476 evacuees left simultaneously. Again, this may not be true in reality, but knowing the exact time each evacuee left was not possible.

Step 6: Most people walk two to three abreast when in groups, even if the group contains more than two to three individuals (Costa 2010). This creates a crowd density of approximately three people per square meter, which is the most common density for urgent, purposeful walking in evacuations (Still 2014). To create this density while calculating travel time for each group of 476 evacuees, first, 476 was divided by three to determine the how many groups of three people abreast were in each of the 56 groups of 476 evacuees (i.e., 158.67 rounded to 159).

Step 7: The model assumed that each of the 159 groups of three evacuees abreast from Step 6 left the stadium at one-second intervals. Thus, the minimum, mean, and maximum evacuation times for each group of 476 evacuees were calculated by adding the respective minimum, mean, and maximum travel time (calculated in Step 4) for the minimum, mean, and maximum locomotion speeds (i.e., from Step 2) to 158 (i.e., 159 groups of three evacuees abreast  $-1$ ; the first group of three evacuees required the minimum, mean, or maximum travel time from Step 4 to evacuate, and each subsequent group left at one-minute intervals afterward, so one minute for each subsequent group was added to the respective minimum, mean, or maximum travel times). These results are Table 13 in Chapter IV.

APPENDIX J Stadium Centroid to Sidewalk Exit Point Raw Data and Intermediate

### Results

The data and intermediate results are listed using each step from Chapter III.

Step 1: The Euclidean distance between the stadium centroid and each sidewalk network exit point (i.e., 66 distances) was measured using the Near tool in ArcGIS (Figure 5 in Chapter II and Table A7 in Appendix J).

Table A7.

*Stadium Centroid to Sidewalk Destination Points Near Analysis Data and Results*

FID2	NEAR FID	NEAR <b>DIST</b>	$t_s$ 1 44	$t_s$ 1 47 $t_s$ 1 51		time_s_ $1_5$
$\theta$	$\overline{0}$	368.094145	255.62093	250.40418	243.77096	245.39610
$\mathbf{1}$	$\theta$	330.526592	229.53236	224.84802	218.89178	220.35106
$\overline{2}$	$\overline{0}$	326.680283	226.86131	222.23149	216.34456	217.78686
3	$\overline{0}$	330.281747	229.36232	224.68146	218.72963	220.18783
$\overline{4}$	$\overline{0}$	334.050853	231.97976	227.24548	221.22573	222.70057
5	$\overline{0}$	362.817474	251.95658	246.81461	240.27647	241.87832
6	$\theta$	474.679303	329.63841	322.91109	314.35715	316.45287
7	$\overline{0}$	644.817121	447.78967	438.65110	427.03121	429.87808
Table A7 (continued).

FID <sub>2</sub>	NEAR <b>FID</b>	NEAR <b>DIST</b>	$t_s_1_44$		$t_s$ $1_47$ $t_s$ $1_51$	time $s \ 1 \ 5$
8	$\overline{0}$	713.581647	495.54281	485.42969	472.57063	475.72110
9	$\overline{0}$	723.728510	502.58924	492.33232	479.29040	482.48567
10	$\overline{0}$	1004.11816	697.30428	683.07358	664.97891	669.41210
11	$\overline{0}$	1015.36516	705.11469	690.72460	672.42726	676.91010
12	$\overline{0}$	1098.83188	763.07770	747.50468	727.70323	732.55459
13	$\overline{0}$	1113.97182	773.59154	757.80396	737.72968	742.64788
14	$\overline{0}$	1247.58769	866.38034	848.69911	826.21701	831.72512
15	$\overline{0}$	1264.19244	877.91142	859.99486	837.21354	842.79496
16	$\theta$	1346.03181	934.74431	915.66790	891.41180	897.35454
17	$\overline{0}$	1363.92346	947.16907	927.83909	903.26057	909.28231
18	$\overline{0}$	1467.99132		1019.4384 998.63355	972.17968	978.66088
19	$\theta$	1451.50128		1007.9870 987.41584	961.25913	967.66752
20	$\overline{0}$	1448.28789		1005.7555 985.22986 959.13106		965.52526

Table A7 (continued).

FID <sub>2</sub>	NEAR <b>FID</b>	NEAR_ <b>DIST</b>	t_s_1_44		$t_s$ $1_47$ $t_s$ $1_51$	time_s_ $1_5$
21	$\overline{0}$	1423.29128	988.39672	968.22536	942.57701	948.86086
22	$\overline{0}$	1420.44654	986.42121	966.29016	940.69307	946.96436
23	$\overline{0}$	1398.29830	971.04049	951.22334	926.02537	932.19887
24	$\overline{0}$	1400.21591	972.37216	952.52783	927.29530	933.47727
25	$\overline{0}$	1364.91958	947.86082	928.51672	903.92025	909.94638
26	$\overline{0}$	1363.67703	946.99794	927.67145	903.09737	909.11802
27	$\overline{0}$	1354.85317	940.87026	921.66882	897.25375	903.23545
28	$\overline{0}$	1355.28606	941.17088	921.96331	897.54044	903.52404
29	$\overline{0}$	1375.56325	955.25226	935.75731	910.96904	917.04217
30	$\overline{0}$	1377.61087	956.67422	937.15025	912.32508	918.40725
31	$\theta$	1426.62478			990.71165 970.49305 944.78462	951.08319
32	$\theta$				1229.82774 854.04704 836.61751 814.45545	819.88516
33	$\overline{0}$	1216.54078			844.81999 827.57876 805.65615	811.02719

Table A7 (continued).

FID <sub>2</sub>	NEAR <b>FID</b>	NEAR <b>DIST</b>	t s $1\,44$	t_s_1_47	t_s_1_51	time_s_ $1_5$
34	$\boldsymbol{0}$	1123.70632	780.35161	764.42607	744.17637	749.13755
35	$\overline{0}$	1116.31337	775.21762	759.39685	739.28038	744.20891
36	$\overline{0}$	1022.73451	710.23230	695.73776	677.30762	681.82300
37	$\overline{0}$	1010.47021	701.71542	687.39470	669.18557	673.64681
38	$\boldsymbol{0}$	964.160939	669.55621	655.89180	638.51718	642.77396
39	$\theta$	950.546678	660.10186	646.63039	629.50111	633.69779
40	$\theta$	915.789457	635.96490	622.98603	606.48308	610.52630
41	$\overline{0}$	908.384334	630.82245	617.94853	601.57903	605.58956
42	$\theta$	822.342392	571.07111	559.41659	544.59761	548.22826
43	$\theta$	812.806506	564.44896	552.92960	538.28245	541.87100
44	$\overline{0}$	729.122610 506.33521 496.00184 482.86272				486.08180
45	$\theta$	720.981233		500.68141 490.46342	477.47102	480.65416
46	$\overline{0}$	648.654823 450.45474 441.26178 429.57273				432.43655

Table A7 (continued).

FID <sub>2</sub>	NEAR <b>FID</b>	NEAR <b>DIST</b>	t_s_1_44	t s 1 47	t_s_1_51	time_s_ $1_5$
47	$\theta$	636.830034	442.24308	433.21771	421.74174	424.55336
48	$\overline{0}$	608.899766	422.84706	414.21753	403.24488	405.93318
49	$\overline{0}$	601.608756	417.78386	409.25766	398.41639	401.07250
50	$\overline{0}$	547.690354	380.34052	372.57847	362.70884	365.12690
51	$\theta$	529.386453	367.62948	360.12684	350.58705	352.92430
52	$\boldsymbol{0}$	478.321081	332.16742	325.38849	316.76893	318.88072
53	$\theta$	475.593242	330.27308	323.53282	314.96241	317.06216
54	$\overline{0}$	469.539719	326.06925	319.41478	310.95346	313.02648
55	$\theta$	467.547418	324.68571	318.05947	309.63405	311.69828
56	$\theta$	459.806697	319.31021	312.79367	304.50775	306.53780
57	$\theta$	478.867809		332.54709 325.76041	317.13100	319.24521
58	$\theta$	461.254966	320.31595	313.77889	305.46687	307.50331
59	$\theta$	402.826319		279.74050 274.03151	266.77240	268.55088

Table A7 (continued).

FID <sub>2</sub>	NEAR FID	NEAR <b>DIST</b>	t_s_1_44	t_s_1_47	t_s_1_51	time_s_ $1_5$
60	$\theta$	388.917798	270.08180	264.56993	257.56146	259.27853
61	$\overline{0}$	341.028975	236.82568	231.99250	225.84700	227.35265
62	$\overline{0}$	321.587272	223.32449	218.76685	212.97170	214.39151
63	$\overline{0}$	196.309444	136.32600	133.54384	130.00625	130.87296
64	$\overline{0}$	188.615989	130.98333	128.31020	124.91125	125.74399
65	$\overline{0}$	205.759941	142.88885	139.97275	136.26486	137.17329

Table A7 (Appendix J) field definitions:

FID2: The feature identification number of each parking lot centroid.

NEAR\_FID: The feature identification number of the stadium centroid.

NEAR\_DIST: The straight-line distance between the NEAR\_FID and each ORIG\_FID in meters.

t\_s\_1\_44: The time in seconds to travel each distance with a locomotion speed of 1.44 meters per second.

t\_s\_1\_47: The time in seconds to travel each distance with a locomotion speed of 1.47 meters per second.

t\_s\_1\_51: The time in seconds to travel each distance with a locomotion speed of 1.51 meters per second.

t\_s\_1\_5: The time in seconds to travel each distance with a locomotion speed of 1.5 meters per second.

Step 2: Minimum, mean, and maximum locomotion speeds for survey participants who indicated that they walked to games (i.e., walk responses to questionnaire Item 9) were calculated.

Step 3: The minimum, mean, and maximum travel times for each of the 66 stadium centroid to sidewalk network exit point distances (i.e., Step 1 results) were calculated by dividing each distance by the minimum, mean, and maximum locomotion speeds from Step 2, as well as a locomotion speed of 1.5 meters per second (e.g., minimum travel time for distance  $1 =$  distance  $1 /$  minimum locomotion speed; see Table A7 (Appendix J), fields  $t_s = 1_44$ ,  $t_s = 1_47$ ,  $t_s = 1_51$ , and  $t_s = 1_5$ , above for these results).

Step 4: The minimum, mean, and maximum travel times for this component (i.e., all of the stadium centroid to sidewalk network exit point location distances) were calculated from the results of Step 3 (i.e., minimum, maximum, and average travel times based on all of the distances for each speed) (Table A8, Appendix J).

Table A8.

*Minimum, Mean, and Maximum Travel Times for Locomotion Speeds of Walking Evacuees*



Step 5: The number of walking evacuees (i.e., 9,356) was divided by the number of sidewalk network evacuation points (i.e., 66) to determine the number of evacuees per lot (i.e., 141.76 evacuees rounded to 142, as fractional numbers of people are not

possible). Although this number was likely, not true in reality, there was no way to know how many evacuees exited via each sidewalk network exit point, so the evacuees were evenly distributed among all of the points. The model assumed that each group of 142 evacuees left simultaneously. Again, this may not be true in reality, but knowing the exact time each evacuee left was not possible.

Step 6: As explained previously, most people walk two to three abreast when in groups, even if the group contains more than two to three individuals (Costa 2010). This creates a crowd density of approximately three people per square meter, which is the most common density for urgent, purposeful walking in evacuations (Still 2014). To create this density while calculating travel time for each group of 142 evacuees, first, 142 was divided by three to determine the how many groups of three people abreast were in each of the 66 groups of 142 evacuees (i.e., 47.33 rounded to 48).

Step 7: The model assumed that each of the 66 groups of three evacuees abreast from Step 6 left the stadium at one-second intervals. Thus, the minimum, mean, and maximum evacuation times for each group of 142 evacuees were calculated by adding the respective minimum, mean, and maximum travel time (Step 4) for minimum, mean, and maximum locomotion speeds (Step 2) to 47 (i.e., 48 groups of three evacuees abreast – 1; the first group of three evacuees required the minimum, mean, or maximum travel time from Step 4 to evacuate, and each subsequent group left at one-minute intervals afterward, so one minute for each subsequent group was added to the respective minimum, mean, or maximum travel times).

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