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PEDESTRIAN DYNAMICS: MODELING AND ANALYZING COGNITIVE PROCESSES AND TRAFFIC FLOWS TO EVALUATE FACILITY SERVICE LEVEL

By

Hohyun Lee

A Dissertation
Submitted to the Faculty of
Mississippi State University
in Partial Fulfillment of the Requirements
for the Degree of Doctor of Philosophy
in Industrial Engineering
in the Department of Industrial and Systems Engineering

Mississippi State, Mississippi

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By

Hohyun Lee

Approved:

____
Lesley Strawderman
Assistant Professor of
Industrial and Systems Engineering
(Committee Chair)

____
Changhe Yuan
Assistant Professor of
Computer Science and Engineering
(Minor Representative)

____
James M. Giesen
Professor of Psychology
(Committee Member)

____
Mingzhou Jin
Associate Professor of
Industrial and Systems Engineering
(Committee Member)

____
John M. Usher
Professor of
Industrial and Systems Engineering
(Committee Member)

____
Edward B. Allen
Associate Professor and Graduate
Coordinator of Computer Science

____
John M. Usher
Professor and Graduate Coordinator of
Industrial and Systems Engineering

____
Sara A. Rajala
Dean of the College of Engineering

Name: Hohyun Lee

Date of Degree: December 9, 2011

Institution: Mississippi State University

Major Field: Industrial Engineering

Minor Field: Computer Science

Major Professor: Dr. Lesley Strawderman

Minor Professor: Dr. Changhe Yuan

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Candidate for Degree of Doctor of Philosophy

Walking is the oldest and foremost mode of transportation through history and the prevalence of walking has increased. Effective pedestrian model is crucial to evaluate pedestrian facility service level and to enhance pedestrian safety, performance, and satisfaction.

The objectives of this study were to: (1) validate the efficacy of utilizing queueing network model, which predicts cognitive information processing time and task performance; (2) develop a generalized queueing network based cognitive information processing model that can be utilized and applied to construct pedestrian cognitive structure and estimate the reaction time with the first moment of service time distribution; (3) investigate pedestrian behavior through naturalistic and experimental observations to analyze the effects of environment settings and psychological factors in pedestrians; and (4) develop pedestrian level of service (LOS) metrics that are quick and practical to identify improvement points in pedestrian facility design.

Two empirical and two analytical studies were conducted to address the research objectives. The first study investigated the efficacy of utilizing queueing network in modeling and predicting the cognitive information processing time. Motion capture system was utilized to collect detailed pedestrian movement. The predicted reaction time using queueing network was compared with the results from the empirical study to validate the performance of the model. No significant difference between model and empirical results was found with respect to mean reaction time.

The second study endeavored to develop a generalized queueing network system so the task can be modeled with the approximated queueing network and its first moment of any service time distribution. There was no significant difference between empirical study results and the proposed model with respect to mean reaction time.

Third study investigated methods to quantify pedestrian traffic behavior, and analyze physical and cognitive behavior from the real-world observation and field experiment. Footage from indoor and outdoor corridor was used to quantify pedestrian behavior. Effects of environmental setting and/or psychological factor on travel performance were tested.

Finally, adhoc and tailor-made LOS metrics were presented for simple realistic service level assessments. The proposed methodologies were composed of space revision LOS, delay-based LOS, preferred walking speed-based LOS, and ‘blocking probability’.

DEDICATION

To my dear wife and beloved children for their unconditional love and support.

한결같은 믿음과 사랑을 보내준 사랑하는 아내 박은정과 소중한 아들 동준, 준혁이에게 이 논문을 바칩니다.

2011 년 11 월 11 일

이호현

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CHAPTER I

INTRODUCTION

1.1 Overview and Challenges in Pedestrian Study

Walking is an innate ability for humans and is the oldest and foremost mode of transportation through history. It is a crucial part of the transportation chain, and the prevalence of walking has increased. According to the '2005 Traveler Opinion and Perception Survey', conducted by the U.S. Federal Highway Administration (FHWA), around 107 million people used walking as a primary means of travel, accounting for approximately 51 percent of travelers (FHWA, 2005). Even with the increased importance of analyzing and modeling pedestrian traffic behavior, pedestrian traffic flows and behaviors have only been paid restricted attention in recent research. One of the reasons is the tools to analyze pedestrian traffic flows and related behaviors are scarce. Interest in the field is growing due to the integral nature of walking as a part of the transportation chain. There is a current need to more accurately depict pedestrian movements and behavioral characteristics to evaluate and improve pedestrian facility design.

Modeling walking characteristics and the environment is not an easy task and has been of interest to researchers for nearly a decade (Helbing & Molnár, 1997; Daamen & Hoogendoorn, 2003; Antonini, Bierlaire, & Weber, 2006). The design of a pedestrian facility should take into account the behavior of the pedestrians utilizing these facilities, as well as interaction with their environment.

The efficiency, safety, and comfort of a pedestrian facility are determined not only by its physical architecture but also by the behavior of the facility's users. The way people walk, choose their paths, and navigate crowds and obstacles impacts the effectiveness of that facility.

When planning pedestrian facilities, designers have generally considered a number of tangible factors, such as facility capacity, volume, and so forth. However, many factors that impact navigational performance have not yet been comprehensively considered in pedestrian models that evaluate pedestrian facility service level. The Highway Capacity Manual (TRB, 2000) defines level of service (LOS) as a quality measure describing operational conditions of vehicular and pedestrian traffic based on service measures, such as "speed, travel time, freedom to maneuver, traffic interruptions, comfort and convenience". Even in the pedestrian study arena, researchers have given limited attention to modeling physical aspects of traffic performance while analyzing and assessing the service quality of pedestrian facilities. Pedestrians are the primary non-motorized users and stakeholders of walking facilities. If researchers do not incorporate pertinent pedestrian navigational characteristic in their models, they cannot expect to obtain practicable outcomes from the models (Bleu et al., 1997; Hoogendoorn & Bovy, 2004; Helbing et al., 2005).

Data and statistics from empirical pedestrian studies are useful when they can be applied to model pedestrian behaviors for a general population. With an appropriate pedestrian model, the behaviors of pedestrians can also be predicted and analyzed. This dissertation research endeavored to develop a pedestrian model that encompasses the pedestrian cognitive processing for visual search, means of traffic flow analysis, and methodology for pedestrian facility service level evaluation. Systems of interest and facility conditions were: (1) pedestrian walkways and corridors under the non-interrupted flow situations; and (2) pedestrian facilities under normal conditions. This study did not take into consideration pedestrian evacuation or egress situation (see TRB, 2000.).

1.2 Research Aims

The objective of this study was the development of an empirically validated pedestrian behavior model that considers cognitive as well as physical aspects of pedestrian behavior, and its impact on facility level of service. The objective encompassed the development of four main analytical tools along with each empirical study, which included: (1) M/G/c queueing system based cognitive information processing model; (2) pedestrian traffic flow analysis and modeling based on empirical studies; and (3) pedestrian level of service (LOS) model developments. Each model was tested and validated through appropriate experiments as illustrated in Figure 1.1. The long-term goal of the dissertation research was to build the framework of pedestrian modeling and analysis tool, so that the pedestrian navigational behavior can be more effectively analyzed and predicted to improve pedestrian facility design.

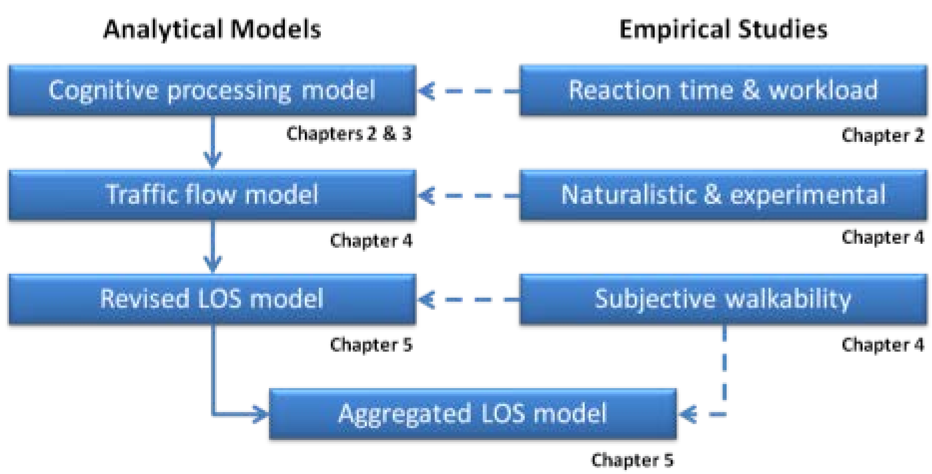

Figure 1.1 Structure of the Study

1.2.1 Study 1: Cognitive Information Processing Model (Chapters II & III)

The first component of the proposed pedestrian model was a representation of a pedestrian's cognitive processing. The application of queueing systems to cognitive information processing has been demonstrated previously in human computer interaction and driver's performance research areas (Liu, 1996; Wu & Liu, 2007). The benefits of incorporating queueing systems into the research framework are: (1) queueing systems are useful to analyze traffic performance to determine the average number of customers (the number of information bits or pedestrians) in the system, average times in system (both in queue and server), and blocking probability; (2) it can be expanded as a network system that comprises interconnected server and customer relationships; (3) it enables inferences of causality by conditioning prior information if servers are linked with other server nodes; and (4) queueing systems model can predict the behavior of systems that attempts to provide service for randomly arising demands. The specific model of interest was the M/G/c queueing system. It is a multi-server system with a Markovian (Poisson arrival process) interarrival time and general service time distributions.

The objective of the first study was to investigate the reaction time (i.e., delay in information processing) from stimuli. The delay is likely compounded by the fact that pedestrians are faced with many more decision points when navigating through a dense crowd. In this case, the reaction time is viewed as a performance measure (e.g., time in system or sojourn time) since the sojourn time is one of the primary outcomes of queueing systems.

Walkers are frequently faced with various stimuli from their environment while they navigate, and they need to process information to complete their travel agenda. Within the queueing network framework, each stimulus was encoded as a customer that is processed by servers. The servers in the queueing network represented pedestrians' information processing units. The stimuli as customers, then, go through the route in the information processing network. The average values such as sojourn time (total reaction time) and the amount of information processed (the number of stimuli) per unit time were investigated. This can then be used as initial pedestrian mental characteristics for traffic performance analysis assuming that these metrics are correlated with pedestrian navigational performance. Finally, the efficacy of queueing modeling of pedestrian navigational performance and mental workload is discussed.

1.2.2 Study 2: M/G/c Queue Approximation and Its Application to Cognitive Information Processing (Chapter III)

Previous researches on cognitive information processing using queueing system made assumptions to represent human information processing system. The method to process information is confined to serial processing for all stages of information processes, such as perceptive, cognitive and motor processes. This assumption may not be appropriate, because peripheral perceptive and motor processes continue in parallel and only a cognitive stage is processed in serial based on neuroscience research (Pashler, 1994; Sigman & Dehaene, 2008). Second, a single server system was applied to structure the information process. Under this assumption, it may not be possible to represent multiple task situations due to its architectural limitation. Third, the methodology assumed the capacity of information processing unit is infinite. This also may violate the well-known theory of limits on human capacity for processing information (Miller, 1956).

A queueing system was derived in order to relax the assumptions in literatures and model the mental process and configure the cognitive structure for pedestrian navigation.

In general, customer arrivals occur irrespective of system activity, which means new customers arrive at the system regardless of the number of customers in the system. Based on this fact, a Poisson arrival process was applied in the study. Since service times, however, may not necessarily be exponential, general service time distributions were applied in this study. As humans perform multiple tasks and facilities serve multiple pedestrians at a time, this research attempts to implement a multi-server system.

The majority of solutions for M/G/c queues are given in the format of complex transform, which requires taking the reverse transform to obtain the solution. It is difficult to determine the exact solution as the system is more complicated with a large number of servers. No exact solutions have been found for M/G/c queueing systems. However, a number of techniques have been presented for the M/G/1 model to obtain exact solutions, such as 'imbedded Markov chain method' and 'supplementary variable technique' (Takagi, 1991; Tijms, 1994; Gross et al., 2008). For this reason, approximate approaches have been attempted to provide quick-and-dirty solutions (Cruz et al., 2005; Cruz & Smith, 2007). To apply a multi-server queueing system with general service time distributions to the pedestrian mental processing and traffic performance models, this research endeavored to obtain the steady state system size (i.e., the number of information bits and/or pedestrians in system) without taking any transforms (e.g., Laplace transform or z-transform). That is, a simple, reliable method to obtain solutions for predicting cognitive information processing time based on queueing network system was aimed. The precision of the approximation algorithm was tested and validated through the comparison of the results from analytical model and simulation runs.

Liu and his colleagues (1996, 2006) proposed the queueing network mental processing model, and primarily focused on M/M/1 based open queueing network, also known as a Jackson network (Jackson, 1963). This methodology is simple and easy to implement, but it has a somewhat large number of nodes (parallel servers) to represent multitasking. Moreover, there is no guarantee that the service time (mental processing time from perceived stimuli to reaction) follows an exponential distribution. The shortfalls of their method can be surmounted by using an M/G/c queueing system, since the inherent feature of this structure allows for the reduction in the number of nodes to construct a mental model, which embraces multitasking in a simple fashion. The effectiveness of the model was tested and validated by investigating the difference between the estimated average reaction time from the model and the direct measurement of reaction time from an empirical study.

1.2.3 Study 3: Pedestrian Traffic Flow Analysis (Chapters IV)

The third objective was to develop an analytical pedestrian traffic performance measure. There are some common approaches to pedestrian behavior modeling, such as cellular automata, social force, magnetic force, queueing network models and so forth. Cellular automata consist of an array of grid cells that represent the pedestrian environment (Blue et al., 1997). Pedestrian agents (each of them occupies a single cell at any given time) accomplish movement using updated localized neighborhood rules. In a social force model, pedestrians are motivated to move in response to attractive and repulsive forces exerted by their surroundings (Helbing & Molnár, 1997). Similarly, a magnetic force model is composed of positive poles and negative poles that represent obstructions and goals, respectively (Matsushita & Okazaki, 1993). In queueing network models, nodes represent the current locations that are linked to define possible routes to navigate (Løvås, 1994; Cruz & Smith, 2007). Previous studies on pedestrian traffic modeling using queueing networks generally represented pedestrian routes by means of a linear fashion (Løvås, 1994; Cruz & Smith, 2007), which is not realistic compared to other methodologies.

Detailed pedestrian traffic performance can be measured based on findings from empirical studies (walking speed, acceleration, trajectory changes, pedestrian density, and pedestrian spacing propensity). The traffic flow model is composed of four main components: (1) the pedestrian arrival rate determined from empirical data; (2) service time (time spent at a node), which is affected by pedestrian density in the region of interest and cognitive processing time (delay) described previously; (3) node (any resource point in the pedestrian facility and rooms); and (4) link (a path between two consecutive nodes). Pedestrians navigate from one node to another (sub-goals) to complete their travel agenda. The queueing system collects traffic data from each node in the events of pedestrian birth (spawning or arrival) and death (exit or departure) as well as from within the node intermediately. This model is expected to provide some critical pedestrian traffic performance information, such as average speed, blocking probabilities for pedestrian navigation, average inter-departure time from node to node, pedestrian density and flow rate, the most congested node, and average time in system (sojourn time). The model will be validated by comparing difference between empirical data analysis results.

Whereas previous researches in the pedestrian literature are mainly focused on the physical aspect of pedestrian traffic performance, this study appended psychological pedestrian characteristics to the research scope. Cognitive behaviors in the study include zone of comfort (Goffman, 1963, 1971; Hall, 1966), situation awareness (Bell & Lyon, 2000), and walkability (Litman, 2007; Reid, 2008). Associations and impacts of cognitive pedestrian behaviors on physical traffic performance were analyzed and discussed.

1.2.4 Study 4: Level of Service Model (Chapter V)

Finally, an assessment methodology of pedestrian facilities was developed to examine facility level of service (LOS). Although there are existing LOS metrics used in the transportation field today, they do not address all of the factors that we have found to impact a pedestrian's facility usage. The current Highway Capacity Manual (HCM) (TRB, 2000) methodology for assessing pedestrian LOS over-simplifies the pedestrian traffic situation, and generalizes conditions with the overall average traffic performances within a certain period of time.

In the study, presenting aggregated LOS metrics were aimed for more realistic service level assessments. The proposed methodology includes revised LOS measures in addition to a subjective measure of LOS (walkability). The aggregated LOS was then developed combining HCM LOS and revised LOS with walkability using the multiple linear regression method. It was expected that the proposed LOS metrics assist in determining the need to redesign the facility layout, including changes of walkway width and relocation or removal of services and amenities.

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CHAPTER II

EFFICACY OF UTILIZING QUEUEING NETWORK TO MODELING COGNITIVE INFORMATION PROCESSES AND PERFORMANCE IN PEDESTRIAN NAVIGATION

2.1 Abstract

This study investigates the efficacy of utilizing queueing network-model human processor (QN-MHP) model, which predicts cognitive information processing time and task performance. Motion capture system was utilized to collect detailed pedestrian movement. Twenty participants, ten male and ten female, completed lab-based navigational tasks under various levels of obstruction density in a constructed walkway. Changes in trajectory and speed, task accuracy, reaction time, and subjective workload under the treatment combinations of obstruction density level and designated speed level were measured and collected to test effects of density and speed on task performance. The predicted reaction time using QN-MHP was compared with the results from the empirical study to validate the performance of the model. No significant difference between speed and space with respect to mean reaction time while efficiency and mental workload measures vary significantly as levels of speed and space change. No significant difference between model and empirical results with respect to mean reaction time was found.

Keywords: motion capture, reaction time, workload, pedestrian navigation, GOMS, QN-MHP.

2.2 Introduction

Human cognition can be defined as the summation of representation of the world and computational processes. Data from the real world represents the system, and a sequence of functional components process the data to reach a goal (Thagard, 2005). To accomplish navigational tasks, pedestrians describe their environment based on the acquired information from their sensory system and decide what to take from the information to build an action plan for navigation (Wickens & Hollands, 1999). When analyzing and modeling cognitive aspects of pedestrian walking behavior, researchers have encompassed a stimulus component in their models (Hoogendoorn & Bovy, 2005; Kachroo et al., 2008; Robin et al., 2009). These models were mainly focused on collision avoidance to source of obstruction (stimulus) without identifying the time to take acquired information for efficient navigation as well as the amount of cognitive load to complete the travel agenda.

This study endeavored to identify theory-based mechanisms of human performance that can account for meaningful performance differences in real-world tasks and settings in order to utilize the selected theoretical mechanism in pedestrian navigation. The primary performance measure in this study was a reaction time. Reaction time is defined as the delay between stimulus presentation and response initiation, which is also interpreted as cognitive processing time (Liu, 1996). The structure of the pedestrian cognitive information processing was constructed, and the computed values of reaction time and formulation of mental workload was also presented and incorporated into the pedestrian model to more accurately depict pedestrian behavior. Even though reaction time and mental workload can be estimated via either symbolism or connectionism model of human performance (Liu, Feyen, & Tsimhoni, 2006), direct measurements of reaction time and mental workload with human subjects were necessary to test factorial effects with respect to the mean responses and to validate the efficacy of model applied.

2.3 Background

2.3.1 Cognitive Models

Human information processing models represent perceptual, cognitive, and motor processes with different stages at which information gets transformed. According to Wickens' work (1984b), information processing can be broken into four discrete areas: perception, memory, decision making, and selection of action. Each of these areas can be further broken down into a variety of components and all of these interact to produce information processing and interaction in human beings. Even though each model in the literature shares similarities and bears differences as well, they usually focus on particular processes. To convey the broader background for this study, the existing cognitive models that employ conceptual, mathematical, and computational frameworks are briefly reviewed.

Conceptual models can be broken down into two major models: Information processing model (Wickens, 1984a, 1984b) and Skill-Rule-Knowledge (SRK) model (Rasmunssen, 1976, 1983). Wickens' information processing model depicts overall aspects that typically influence human cognition (e.g., perceiving, thinking about, and understanding the system). This model also includes simple human information processing units, sequences, and environmental factors that impact the process, speed, and quality of response execution. Wickens' model is useful for conceptual understanding of cognition, but lacks in providing quantitative values of human performance. Likewise, Rasmunssen's SRK model describes the sequence of information processing with respect to knowledge, rule and skill-based behaviors that elucidates dependency of decision making on the decision context. This model is consistent with accepted and empirically supported models of cognitive information processing (Fitts, 1966; Anderson, 1996), and has been applied to a situation awareness model (Endsley, 1995) within a decision making framework (e.g., expert or novice decision making).

Using mathematical models, a simple but rigorous prediction of information processing time (e.g., reaction time or movement time) can be obtained in terms of decision complexity or index of difficulty (Card et al., 1983; Wickens & Hollands, 1999). This category encompasses the Hick-Hyman law (Hick, 1952; Hyman, 1953) and Fitts's law (Fitts, 1954). The Hick-Hyman law (Hick, 1952; Hyman, 1953) enables researchers to characterize the dependency of response selection time on decision making, which formularizes: RT = a + bLog2 N, where RT is reaction time; a and b are constants; and N represents complexity. The formula transforms a simple linear relationship between reaction time and complexity, but the model does not imply that systems designed for users to make simpler decisions are superior (Wickens & Hollands, 1999). These mathematical models are simple and appropriate to compute the overall reaction time with less amount of computational effort, but not suitable for studying cognitive architecture in human information processing.

The last group is classified as computational models. Computational cognitive models are focused on cognitive architectural formations that cover a short period of execution time (e.g., a key-stroke task). This category embraces numerous techniques as shown in Table 2.1. The MHP (Model Human Processor) of Card, Moran, and Newell

(1983) was developed as an engineering human performance and human-computer interaction (HCI). MHP includes a set of processor (i.e., perceptual, cognitive, and motor processors) with memory stores. Card, Moran, and Newell also constructed GOMS (goals, operators, methods, and selection rules) family models which are appropriate for a keystroke level model with a similar structure to MHP. The revised GOMS family models contributed by John and Kieras (1996) was NGOMSL (the natural GOMS Language), which enables GOMS-styles modeling with a more specific task analysis. The EPIC (Executive-Process Interactive Control) (Kieras & Meyer, 1997) model is similar to MHP, but it provides a production rule interpreter and unlimited cognitive resources allowing parallel processes, which are supported by recent empirical and theoretical consequences on human performance in a computer software based task. Unlike EPIC, The ACT-R (Adaptive Control of Thought-Rational) (Anderson et al., 1997; Anderson & Lebiere, 1998; Anderson et al., 2004) model proposes serial discrete processes and it includes two types of memories (i.e., procedural memory and declarative memory) and goal stack. ACT-R sets a single goal that fires a single production system at any point in time and has been described as an integrated (Anderson et al. 2004) and unified (Newell 1990) theory of cognition. Micro Saint (Barnes & Laughery, 1996; Laughery, 1999) and COGNET (Zachary et. al., 1998) are simulation models of human performance that are focused on computing operator workload and problem-solving performance. While Micro Saint covers parallel processing with switching to limited serial resources, COGNET deals with serial processing with switching and interruptions. When representing multitask resources (which are simultaneously allocated to multiple tasks), Micro Saint utilizes visual, auditory, cognitive and psychomotor workload, while COGNET considers limited attention and parallel motor/perceptual processes. Queueing network (QN) modeling of mental processes was proposed by Miller (1993) and Liu (1996). The QN model was recently expanded to the QN-MHP (Queueing Network-Model Human Processor) model (Feyen & Liu, 2001; Liu et al. 2006) that represents the human information processing system as queueing network servers. The QN-MHP model was developed as context-free queueing network architecture (Feyen & Liu, 2001), and was implemented to driving (Wu et al., 2008) and visual search (Lim &Liu, 2004). This model is composed of three subnetworks: perceptual, cognitive, and motor subnetworks. QN-MHP is focused on computing time to perform the task (e.g., reaction time), accuracy in the task and the level of mental workload. The summarized comparison table of cognitive models is displayed in Table 2.1.

Table 2.1 Cognitive Models: Classification and Effectiveness / Issue

Category	Techniques	Effectiveness/Issue
Conceptual models	• Information processing model: (Wickens, 1984a, 1984b) • SRK model: (Rasmunssen, 1976, 1983)	– Describes overall sequence of information processes and their relationships. – Lacks in obtaining quantitative value of information processing time.
Mathematical models	• Fitts's law: (Fitts, 1954) • Hick-Hyman law: (Hick, 1952; Hyman, 1953)	– Provides simple, but rigorous predicted value of information processing time. – Shows the dependency of response selection time on decision making. – Does not guarantee to make simpler decisions are superior.
Computational models (architectural)	• MHP/GOMS: (Card et al., 1983) • GOMS/NGOMSL: (John & Kieras 1996) • EPIC: (Kieras & Meyer, 1997) • ACT-R: (Anderson et al., 1997; Anderson & Lebiere, 1998; Anderson et al., 2004) • Micro Saint (Laughery, 1999; Barnes & Laughery, 1996) • COGNET (Zachary et. al., 1998) • QN-MHP (Liu, 1996; Feyen & Liu, 2001; Lui et al. 2006)	– Requires detailed analysis of short term level interactions (not applicable to long term level tasks) – Improves productivity. – Enables context-free approaches or ignores contextual factors (GOMS, QN-MHP) – Enables to predict information processing time and level of workload (QN-MHP, Micro Saint and COGNET). – Relatively difficult to implement systemically.

2.3.2 Reaction Time: Speed of Cognitive Process

The phenomenon of the gap n time between stimulus presentation and response initiation is frequently observed. The gap can be thought of as the time to execute a response after receiving sensory cues (e.g., visual, auditory, tactile, etc.). Wickens and Hollands (1999) defined that the sum of the duration of a number of component processing stages equals total reaction time. Reaction time also can be interpreted as a cognitive processing time, since the delay occurs due to the fact that some amount of time is required to process information (cognitive load) from exterior stimuli and initiate, whether or not, appropriate responses (physical load). Including reaction time and workload as the factors in pedestrian traffic model would be a more realistic representation of pedestrian behavior. Even though reaction time and mental workload can be estimated using queueing systems (Wu et al., 2008), direct measurements of reaction time and mental workload with human subjects are necessary. This research aims to validate the efficacy of applying the queueing network model in pedestrian collision avoidance behavior with respect to reaction time, as well as to fit the service time distributions at server stations in subnetworks appropriately.

Luce (1986) categorized types of reaction time with respect to measurement methods: simple reaction time, choice reaction time, and recognition reaction time. Simple reaction time is the time required to show a single response from a single stimulus source. In choice reaction time experiments, the operator should show distinct responses corresponding to each possible class of stimulus, as in a simple keystroke-level task. Recognition reaction time task involves determining an appropriate response to a stimulus, such as symbol and tone. In comparing the length of reaction time, Donders (1868/1969) claimed that choice reaction time is longest, and simple reaction time is shortest.

In the pedestrian research arena, the examples of inclusion of a stimulus component in pedestrian agents can be found in Hoogendoorn and Bovy (2005), Kachroo et al.(2008); and Robin et al.(2009). The similarity of these approaches is to construct a delay function with respect to direction and walking speed. However, these models do not explain the source and amount of delay in each cognitive information processing unit, nor do models provide validation of the delay functions with empirical results.

2.3.3 Subjective Workload

As described previously, including a mental workload factor for modeling pedestrian traffic behavior with physical characteristics from empirical study could allow more realistic representation of pedestrian navigation. This section briefly reviews workload measurement techniques to provide backgrounds for measuring and analyzing mental workload.

Various techniques for measuring mental workload exist and can be categorized into primary task measures, secondary task measures, physiological measures, or subjective measures. For each measurement category, there are issues with data collection and the establishment of a relationship to workload as described in Table 2.2.

Table 2.2 Workload Measurement Techniques and Issues

Technique	Description	Issue
Primary task measure	Primary task measures evaluate the most directly related task performed on the system or operator such as computer data-entry speed, driving deviations from the center of the lane, or learning comprehension with a particular method of instruction (Wickens & Hollands, 1999).	A problem with primary workload measures is that they are task-specific. The primary task measure is not a workload measure by itself, since it is affected by mental workload (Sanders &McCormick, 1993).
Secondary task measure	These measures ask an operator to perform the primary task along with a secondary task, causing the operator to use his/her spare attention or capacity to perform a secondary task (Gawron, 2000).	Though the secondary task methods measure demands imposed by the primary task, it seems intrusive to operators performing tasks (Wickens & Hollands, 1999).
Subjective task measure	Subjective measures quantify mental workload by rating workload on a subjective scale. The rating relies on subjective perception of mental workload based on an operator's actual experience (Sheridan, 1980; Wickens et al, 2004).	Subjective measures also have the limitation that human's subjective perception does not always coincide with their task performance (Andre & Wickens, 1995) because subjective perception can be affected by many factors such as an operator's emotion, fatigue, stress, etc.
Psychological measure	Physiological measures quantify mental workload with a single-resource model of information processing, such as heart rate, blink rate, or EEG recording (Sanders & McCornick, 1993; Kramer, 1987).	Physiological measures may impose limitations on task performance as well as physical discomfort, fatigue and contact stress (Kataoka et al, 1998; Genno et al., 1997a).

Primary task measures are associated with evaluating performance measures on the major task of the operators, such as typing speed, yaw and pitch for airplanes, or learning comprehension with a particular method of instruction (Wickens & Hollands, 1999). As cognitive demands of a task change, changes in operator performance can be detected by primary task measures (Tsang & Vidulich, 2006). The primary problem with using primary task measures for mental workload measurement is that they are task-specific, making it difficult to compare between different tasks (Sanders & McCormick, 1993).

Secondary task measures are some of the most widely used mental workload measures. These measures ask an operator to perform a task in addition to their primary task, thereby requiring operators to allocate spare capacities or attentional resources to complete the secondary task (Gawron, 2000). If performance on the primary task requires higher mental workload, there are fewer mental resources available for the completion of the secondary task. Secondary task measures are more sensitive in measuring mental workload than primary task measures because they are believed to demonstrate difficulty level differences between primary tasks (Wickens et al, 2004; Slocum et al., 1971; Gawron, 2000). However, it may be infeasible to impose a secondary task due to the criticality of the primary task (driving, flying, emergency medical technician, etc.). Therefore, the applicability and utility of these measures are limited.

Subjective measures ask operators to rate their mental workload, typically on a scale, based on their subjective perceptions of their experience (Sheridan, 1980; Wickens et al, 2004). The advantage of these methods is they are easy to administer and to obtain ratings (Sanders & McCormick, 1993; Casali & Wierwille, 1983). Some measures elicit a unidimensional rating of mental workload (e.g., the Modified Cooper Harper Scale, Wierwille & Casali, 1983), whereas others combine ratings along multiple dimensions (e.g., the NASA Task Load Index, Hart & Staveland, 1988; or Subjective Workload Assessment Technique, Reid & Nygren, 1988). One limitation of subjective workload measures is that operators' perceptions of mental workload do not always coincide with task performance (Andre & Wickens, 1995). Further, mental workload ratings can be influenced by other factors not related to the task, such as emotional stress, fatigue, etc. (Gaillard, 1993; Wickens et al., 2004). It also is difficult to distinguish external task demand difficulty from actual workload if the tool questions or scales are not well defined (O'Donnell & Eggemeier, 1986).

Physiological measures quantify mental workload with a single-resource model of information processing (Sanders & McCornick, 1993; Kramer, 1987; Tsang & Vidulich, 2006). The central nervous system (CNS) includes the brain, brain stem, and spinal cord cell, and CNS measures are used to detect brain activity. Activities for the CNS can be autonomic (such as heart rate changes and blood vessel constriction/dilation) or voluntary (such as muscle contractions). It is the autonomic responses that are of most interest in mental workload measurement as these are physiological responses that are not controlled or influenced by conscious activities. The autonomic nervous system (ANS) is divided into the sympathetic nervous system (SNS) and parasympathetic nervous system (PNS). SNS provides extra activation to the body in emergency situations (stress state) involving a fight-or-flight reaction while PNS helps to maintain homeostasis limits within the body system by relaxing the body as a regulatory system. Mental stress and emotional state are strong triggers to activate the SNS. SNS stimulation increases mental activity, heart rate, and pupil size. It also contracts the smooth muscle of the organs that constricts blood vessels and pores in the skin. Vasoconstriction is related to decreases in skin surface temperature due to decreased blood flow in tissues. On the other hand, PNS leads to decreased heart rate and pupil size, but it has no effect on mental activity, muscle, or skin (Guyton & Hall, 2006). Even though physiological measures have been used because of problems with intrusiveness and multiple resources in other methods (Tsang

& Wilson, 1997), these methods may impose limitations on task performance as well as physical discomfort, fatigue and contact stress.

2.4 Objectives

The overall objective of this study was to conduct an empirical study to identify appropriate factors that explain characteristics of pedestrian behavior in order to build legitimate pedestrian models with a micro-level of measurement pedestrian reaction time. The study also involved in modeling and constructing cognitive information processes for task performance in terms of reaction time from a given stimulus to collision avoidance action taken in pedestrian navigation so as to provide a credible way of predicting the task performance. There were two specific aims in this study: (1) utilizing motion capture system to collect the precise pedestrian movement and analyze behaviors with respect to reaction time, efficiency, and mental workload on a navigational task; and (2) validating the queueing network based cognitive information processing model through the use of empirically collected data (i.e., predicted versus measured values)

2.5 Hypotheses

The problem of interest is to identify the effect of density and designated walking speed in performance measures. Are the tasks performances in reaction time and efficiency affected by obstruction density level and/or designated speed class? The measured mean reaction time and mean efficiency were compared under each treatment combination of density and speed. The difference between estimated and measured values with respect to reaction time was also tested to validate the efficacy of using queueing network model in pedestrian navigation. Specific hypotheses include:

H1. Density level and speed class do not interact to affect performance measures (reaction time and efficiency).

H2. Density level will affect the performance measures (reaction time and efficiency)

H3. Walking speed will affect the performance measures (reaction time and efficiency)

H4. No gender difference will be found in task performance (reaction time and efficiency)

H5. Performance measures (reaction time and efficiency) will be correlated with workload level

H6. No difference between measured and predicted values of reaction time will be found

2.6 Methodology

2.6.1 Experimental Design

A 3*3 factorial arrangement of treatments on speed and density with three replications was made in random order to assess task performance measures (reaction time and efficiency) and subjective mental workload. Gender was treated as a block to conduct an auxiliary test for variation due to gender. Exposure to trials will be determined using a randomized complete block scheme.

2.6.2 Participants

Twenty participants, ten males and ten females, completed the experimental protocol. Non-impaired (mobility and color blindness) participants who do not wear glasses were recruited from the Mississippi State University student community. Sample size was based on Wu & Liu (2008), which used similar methodology to the one proposed in this study.

2.6.3 Task Description

The study employed a simplified pedestrian navigation situation, which was motivated from pedestrian simulation validation research focused on the discretized angular choice set (Antonini et al., 2006; Robin et al., 2009) and experimental psychology work related with spatial behavior experiment with directional sense measurement (O'Keefe & Nadel, 1978). Participants were asked to complete a walking task avoiding collision under the various level of density (the number of illuminated lamps per area of region of interest; shown as yellow circles in Figure 2.1) at designated speed (i.e., slow, normal, and fast at participants' own judgment) as illustrated in Figure 2.1. While walking, lights were be randomly illuminated to assign density levels. Participants were asked to finish walking tasks when they reach at the end of the site, and to ignore unlit lights.

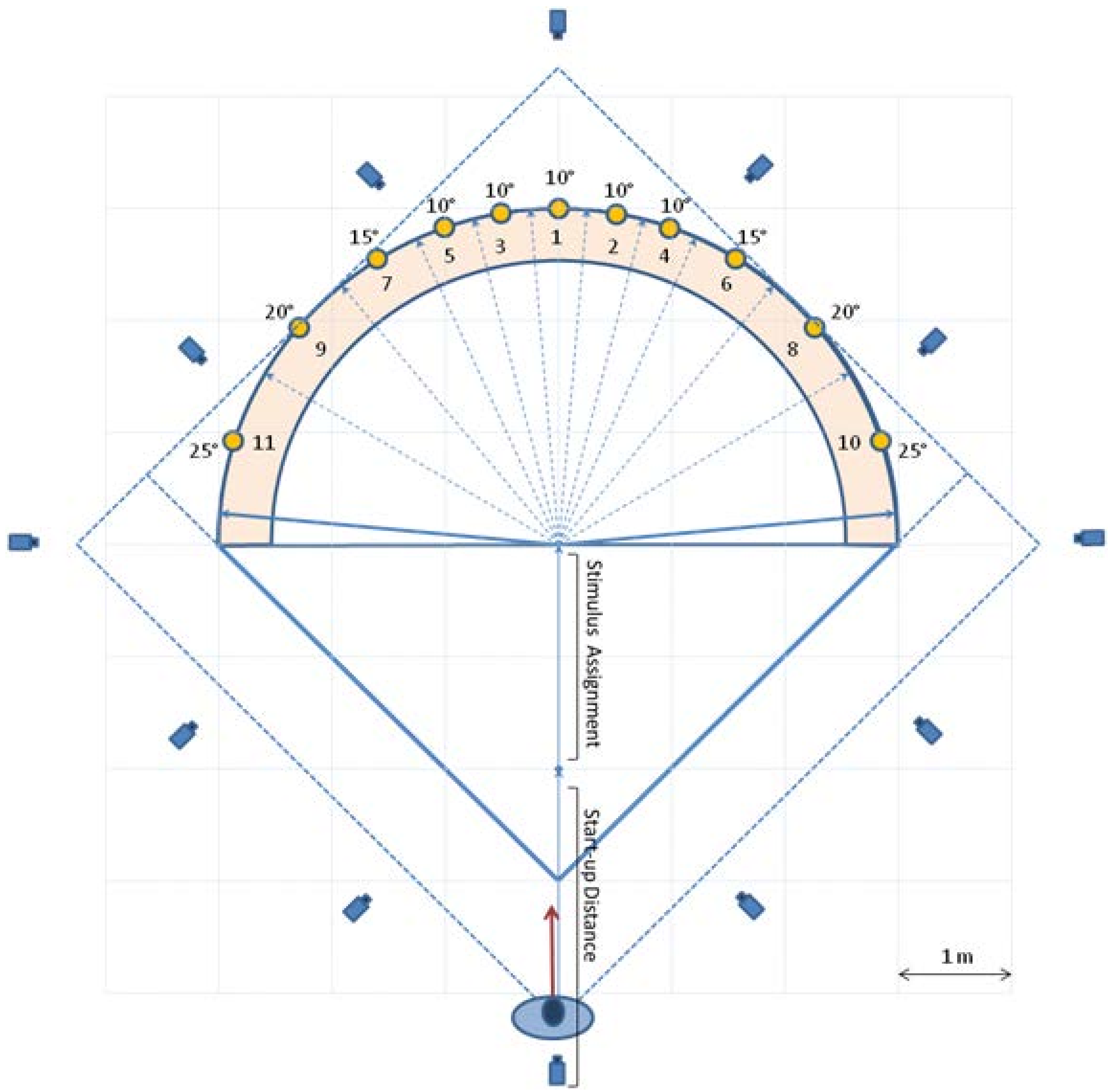

Figure 2.1 Designation of Experimental Site and Region of Interest (ROI)

The distance between stimulus initiation and stimulus (light) was set based on pedestrian "spatial bubble" (Dornfeld, 1997) as illustrated in Figure 2.2. It is defined as the preferred distance of unobstructed forward vision while walking under various circumstances. It categorizes bubbles into four cases that are comfortable for a public event, shopping, normal walking, and pleasure walking for the average pedestrian. The distance between the beginning of stimulus initiation and the blue dotted arc was about 5 m, which corresponds to the normal walk situation (4.6 m – 5.5 m) in Dornfield (1997) and sight distance (4 m) in Teknomo (2006). Upon completion of each trial, participants also completed a subjective workload questionnaire using the computer-based NASA-TLX (Hart & Staveland, 1988).

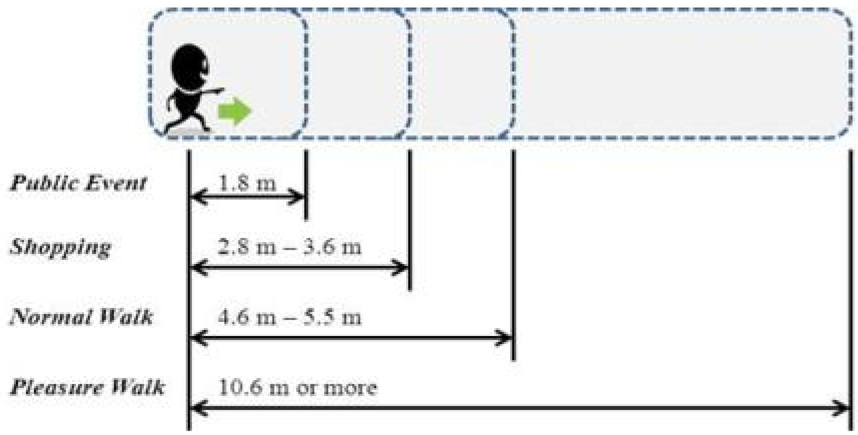

Figure 2.2 Spatial Bubble with Forward Clear Space (Dornfeld & Conroy, 1997)

2.6.4 Independent Variables

Speed class and pedestrian space level were considered as independent variables. Speed class was composed of three levels, such as slow, normal and fast at participants' judgment of each speed, and space had three levels (A, B, and C) based on pedestrian level of service (LOS) category in the Highway Capacity Manual (TRB, 2000) as shown in Table 2.3. The Highway Capacity Manual defines pedestrian LOS as follows: space level A (pedestrian space > 5.6 m^2 / ped) indicates that pedestrians move in desired paths without altering their movements in response to other pedestrians; at level B (3.7 m^2 / ped – 5.6 m^2 / ped), there is sufficient area for pedestrians to select walking speed freely to bypass other pedestrians, and to avoid crossing conflicts; and under the level C (2.2 m^2 / ped – 3.7 m^2 / ped), pedestrians walk with sufficient space at normal speed. Within each treatment combination, participants were asked walk at different speed (slow, normal, and fast). That is to say, each participant performed the same task at three different walking speeds, once under each density level. Three replications were completed for each treatment combination, leading to a total of 27 trials for each participant.

Table 2.3 Speed and Space on Each Navigational Task

		Speed		
		Slow	Normal	Fast
Space LOS	A	Tasks 1-3	Tasks 4-6	Tasks 7-9
	B	Tasks 10-12	Tasks 13-15	Tasks 16-18
	C	Tasks 19-21	Tasks 22-24	Tasks 25-27

2.6.5 Dependent Variables

Dependent variables for this study were reaction time, efficiency, and subjective mental workload. Reaction time and efficiency were measured using motion capture data, which were recorded during the trials and subjective mental workload was assessed after each trial.

Reaction time. A 14-camera motion capture system (Motion Analysis, EVaRT 4.6, 3636 N. Laughlin Road, Suite 110 Santa Rosa, CA 95403) was used to capture participants' motions as illustrated in Figure 2.3. Motion data were collected at a rate of 60 Hz for each task. Six small markers (one fourth to one inch in diameter) were affixed to the head (three markers) and shoulder/neck (three markers) of the participant using recommended procedures. Marker surfaces were covered with retroreflective tape allowing cameras to track marker positions within a three dimensional volume. While participants navigate, a random number of stimuli (light sources) based on LOS level were given to participants. The source of stimulus was a fluorescent lamp that represents other pedestrians in the walkway segment. It was announced to participants that illuminated lights represent other pedestrians which should be avoided. Participants were asked to ignore lights that were not illuminated during the trial.

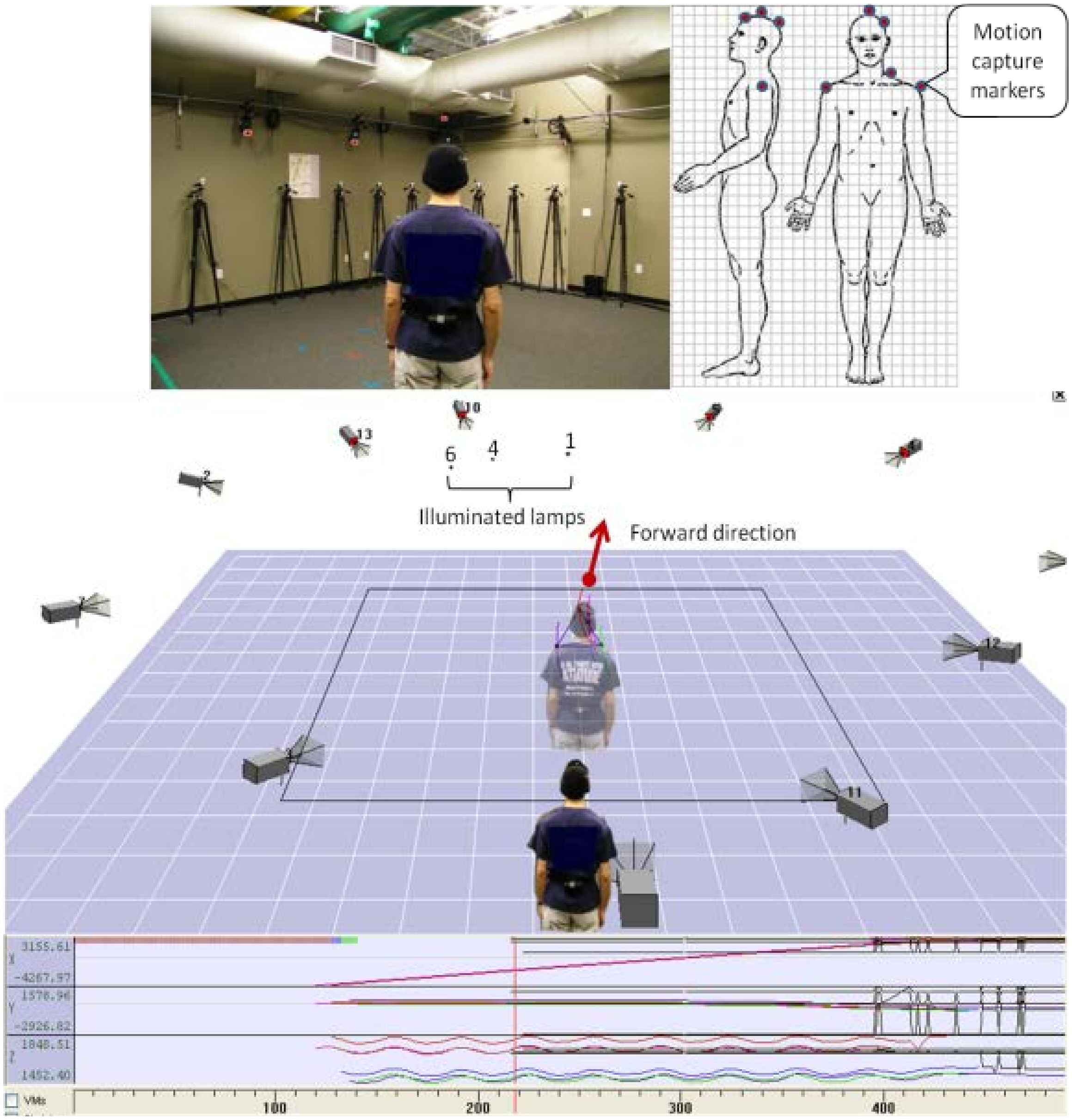

Figure 2.3 Motion Capture Camera, Motion Capture Marker, and Lamp Placement and Sample Pedestrian Motion Recording of Forward Movement

Reaction time was measured using motion capture data, which recorded coordinate data at a frame rate of 60 per second under the three-dimensional Cartesian coordinate system as shown in the bottom of Figure 2.3. Since this study primarily focused on changes in forward walking directions of pedestrians, data on x-axis and y-axis were used projecting those onto the floor (z=0). The measure reaction time in this context is the gap in time between stimulus presentation (the moment of light illumination) and response initiation (changes in both angular velocity and walking speed). Changes in angular velocity were measured by calculating angular acceleration between two consecutive frame data on forehead and acromion angles. Reaction time was measured, when both angular acceleration and walking acceleration were greater and less than their means ± standard deviations respectively. The base time unit of reaction time in 16 milliseconds was used, since that of ACT-R is 15 milliseconds (Anderson et al., 1997). To compare reaction times from the empirical study and QN-MHP prediction, reaction time was also predicted using QN-MHP model (Wu & Liu, 2008) with GOMS style task description. Measuring reaction time enables to develop micro-level pedestrian behavioral modeling that explains pedestrian information processing (Zacharias et al., 2008). Since limited attention has been given in micro-level of pedestrian behavior study (Lee et al., 2008), the inclusion of a GOMS style task description will improve the pedestrian behavior model, because GOMS has been frequently utilized to train young pedestrians for their safety (van der Molen et al., 1983; van der Molen, 2006) and pedestrians who have developmental disabilities (Batu et al., 2004).

Efficiency represents the proportion of the difference between displacement and actual walking distance to displacement (i.e., (displacement – distance) / displacement; and). A displacement is the shortest distance from the initial and final positions of a pedestrian. Thus, it is the length of an imaginary straight path, typically distinct from the path actually travelled by a pedestrian. Whereas, a distance is a scalar measure of the interval between two locations measured along the actual path connecting them. The observed distance would increase, if a pedestrian changed his/her walking trajectory frequently. Since trajectory change is one of the major factors that impacts pedestrian walking performance (Antonini et al., 2006; Teknomo, 2006), the effect of trajectory change (i.e., efficiency) was considered in this study. If a pedestrian walked efficiently with less number of trajectory changes, efficiency would approach to zero. Otherwise, efficiency measure would take a negative value, since distance is usually greater than displacement.

Subjective workload was measured using six scales of NASA-TLX (Hart & Staveland, 1988) after each trial. The NASA-TLX measures mental, physical, and temporal demands, as well as, performance, effort, and frustration levels. These demands were differently weighted based on pedestrian ranking of workload demand component and merged into a single workload index.

2.6.6 Procedure

Upon arrival, participants were given a verbal description of the study and asked to complete informed consent documents. They were given a training session before the actual task are assigned. Each participant was asked to respond to the computer-based NASA-TLX subjective workload rating questionnaires, followed by walking under the given treatment combinations with respect to levels of density and speed. At the moment of experiment completion, participants were compensated for their participation.

2.6.7 Data Analysis

Appropriate descriptive statistics were obtained for each dependent variable (e.g., means and standard deviations). Reaction time was measured counting the number of frames (sixty frames per second) between the frames of stimulus presence and significant changes in forward angle and speed as defined previously. Reaction time was then calculated by multiplying the number of frames by 0.0167. The same manner was applied to calculate efficiency rates as described earlier. A regression model was developed to walking speed function of reaction time, efficiency rate, mental workload and gender.

Multivariate analysis of variance (MANOVA) with performance measures was taken to test hypotheses described previously. Factorial ANOVA was used to assess factorial effects of density and speed level combinations with respect to mean performance measures. As well, Fisher's protected LSD (least significant difference) and Tukey's HSD (honestly significant difference) post hoc tests were used where appropriate. Correlations between each of the dependent variables were computed. All findings were considered significant at an alpha (significant level) of 0.05 unless otherwise stated. The SAS 9.2 for windows was used for all statistical analyses.

2.7 Results

Descriptive statistics for each of the dependent variables are provided in Table 2.4. These statistics contain reaction time in second, efficiency, and workload considering treatment combinations of speed and space levels, as well as gender. The measured overall average (standard deviation) reaction time, efficiency, and subjective mental workload were 0.5089 (0.3924) seconds, -0.0152 (0.0210), and 22.52 (14.90) respectively.

Table 2.4 Descriptive Statistics for the Dependent Variables (N=540)

Gender	Speed	Space	Reaction time (s)		Efficiency		Workload	
			Mean	SD	Mean	SD	Mean	SD
Female	Slow	A	0.6639	0.8109	-0.0158	0.0342	22.6333	12.6973
		B	0.4750	0.2861	-0.0145	0.0129	23.4222	12.9262
		C	0.5800	0.7953	-0.0134	0.0108	23.1333	11.8992
	Normal	A	0.4100	0.1981	-0.0077	0.0051	21.4778	11.7905
		B	0.4606	0.1633	-0.0072	0.0079	21.8556	12.6548
		C	0.5378	0.5602	-0.0216	0.0500	24.9000	13.3523
	Fast	A	0.4295	0.1974	-0.0088	0.0133	29.8000	16.5046
		B	0.5122	0.3524	-0.0060	0.006	27.6555	16.5361
		C	0.5217	0.4318	-0.0125	0.0184	28.8222	15.4038
	Female overall		0.5101	0.4817	-0.0119	0.0227	24.8556	13.9749
Male	Slow	A	0.4961	0.2208	-0.0197	0.017	15.2889	10.6870
		B	0.4306	0.2200	-0.0199	0.0127	15.0667	10.6103
		C	0.5528	0.3278	-0.0248	0.0234	17.8667	13.7014
	Normal	A	0.4745	0.2461	-0.0163	0.0122	13.5222	9.0489
		B	0.5139	0.2539	-0.0168	0.016	16.8222	11.1801
		C	0.5206	0.2863	-0.0205	0.0173	18.8000	12.2292
	Fast	A	0.4856	0.1890	-0.0124	0.0133	28.6556	22.8358
		B	0.4995	0.2547	-0.0158	0.0233	28.7111	19.0250
		C	0.5961	0.4225	-0.0208	0.0263	26.8333	15.7499
	Male overall		0.5077	0.2765	-0.0185	0.0186	20.1741	15.4517
Overall			0.5089	0.3924	-0.0152	0.0210	22.5148	14.9035

When participants walked under the situation of space level A, the measured average (standard deviation) reaction time, efficiency, and workload were 0.4932 (0.3866) seconds, -0.0134 (0.0184), and 21.89 (15.69) respectively. Other space levels were assigned and task performances were also obtained: for space level B, average reaction time, efficiency, and workload were 0.4819 (0.2596) seconds, -0.0134 (0.0184), and 21.89 (15.69) respectively; and when pedestrians walked under the space level C setting, the recorded performance measures with the same order of appearance as levels A and B were 0.5514 (0.4939) seconds, -0.0189 (0.0273), and 23.39 (14.17).

The measured reaction times in second at each speed class, such as slow, normal, and fast, were 0.5330 (0.5111), 0.4862 (0.3113), and 0.5074 (0.3229) respectively. When it comes to efficiency measure with the same order of speed classes as reaction time, descriptive statistics showed -0.0179 (0.0202), -0.0149 (0.0237), and -0.0127 (0.0184). For mental workload index, it indicated that 19.56 (12.50), 19.56 (12.19), and 28.41 (17.63).

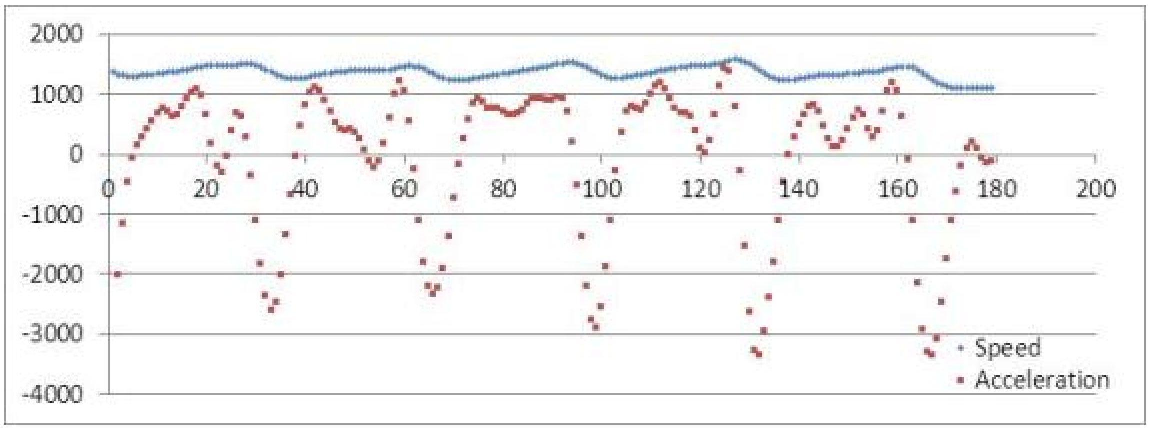

Figure 2.4 Average Speed and Acceleration by Time in Seconds

The observed average (standard deviation) walking speed and acceleration were 1.3729 (0.1052) m/s and -0.090 (1.2187) m/s2 respectively as illustrated in Figure 2.4.

Box-Cox transformation was performed, since the variables did not hold linearity and homogeneity of variance assumptions. The obtained λ's for reaction time, efficiency, and workload that minimize root mean squared errors were -0.6, 0, and 0 respectively. Then these λ's were plugged into the following Box-Cox power function to conduct statistical analysis appropriately.

$$y_{trans} = \begin{cases} \dfrac{y^{\lambda} - 1}{\lambda}, & \lambda \neq 0 \\ \ln(y), & \lambda = 0 \end{cases} \tag{2.1}$$

Tests for homogeneity of variance using Levene's method showed that transformed dependent variables held homoscedasticity assumption. The tests of homogeneity of variance for reaction time ($F(8,531) = 0.88$, $p = 0.5345$), efficiency ($F(8,531) = 1.24$, $p = 0.2727$), and workload ($F(8,531) = 0.93$, $p = 0.4929$) showed conducting ANOVA is reasonable.

Collected data were initially analyzed using two-way MANOVA, factorial arrangement of treatment in a randomized complete block design (gender was treated as a block). This analysis revealed significant multivariate effects for levels of speed and space with respect to average reaction time, efficiency, and workload, Wilk's lambda for overall speed effect = 0.86 ($F(6,1056) = 13.50$, $p < 0.0001$) and Wilk's lambda for overall space effect = 0.98 ($F(6,1056) = 2.16$, $p = 0.04$).

Univariate ANOVAs were also conducted after rejecting multivariate effects. ANOVA resulted that speed and space do not interact to significantly affect mean reaction time ($F(4,530) = 1.20$, $p = 0.31$), efficiency ($F(4,530) = 0.84$, $p = 0.50$), and workload ($F(4,530) = 0.51$, $p = 0.73$) as shown in Table 2.5. No significant differences in speed ($F(2,530) = 0.09$, $p = 0.92$), space ($F(2,530) = 0.66$, $p = 0.52$) and gender ($F(1,530) = 2.97$, $p = 0.09$) with respect to mean reaction time in pedestrian walking were found. For mean efficiency measure, at least two speed levels ($F(2,530) = 18.00$, $p < 0.0001$) and space levels ($F(2,530) = 4.55$, $p = 0.01$) were significantly different. Variation due to gender ($F(1,530) = 73.72$, $p < 0.0001$) was also significant. However, only speed levels ($F(2,530) = 22.82$, $p < 0.0001$) were significantly different with respect to mean workload. Significant variation due to gender ($F(1,530) = 26.33$, $p < 0.0001$) in workload was found.

Table 2.5 Factorial ANOVA Results (p-values)

Dependent Variables	Speed	Space	Speed*Space	Gender
Reaction Time	0.9184	0.5155	0.3111	0.0852
Efficiency	**<0.0001**	**0.0109**	0.4983	**<0.0001**
Workload	**<0.0001**	0.2253	0.7292	**<0.0001**

Note. Bold values indicate significant findings (p-value < 0.05)

2.7.1 Reaction Time Measures

Reaction time was not found to be affected by gender (Table 2.5). Figure 2.4 shows the trend of reaction time in gender. The average (standard deviation) reaction times for female and male walkers were 0.5101 (0.4817) seconds and 0.5077 (0.2764) seconds respectively.

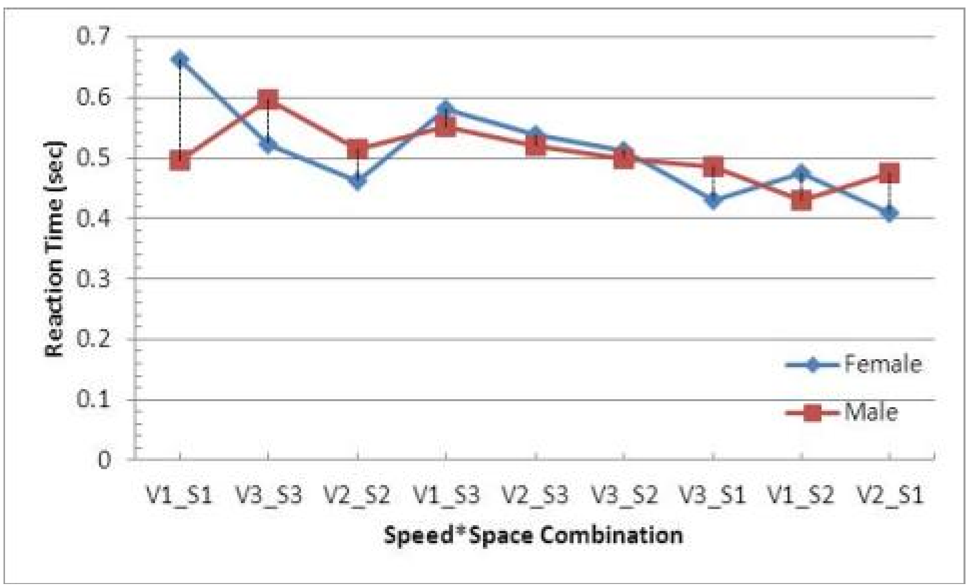

Figure 2.5 Reaction Time Trends in Gender Based on Speed*Space Combination

Note: V1, V2, and V3 indicate slow, normal, and fast walking speeds respectively. S1, S2, and S3 denote space levels A, B, and C correspondingly.

There was no significantly higher or lower reaction time when levels of speed and space change as shown in Table 2.6.

Table 2.6 Tukey's Post-Hoc Comparisons for Reaction Time

Treatment combination (Speed_Space)	Mean	N	Groups
V1_S1	0.5800	60	A
V3_S3	0.5589	60	A
V2_S2	0.4872	60	A
V1_S3	0.5664	60	A
V2_S3	0.5292	60	A
V3_S2	0.5058	60	A
V3_S1	0.4575	60	A
V1_S2	0.4528	60	A
V2_S1	0.4422	60	A

Each mean reaction time reported in Table 2.6 was taken a reverse transformation from the transformed data to show each value in an actual unit of measure (in second), but the rank of each treatment combination was obtained from mean values calculated using the transformed data. The same manners of reporting the multiple comparison results were applied hereafter (i.e., efficiency and mental workload measures).

2.7.2 Efficiency Measures

Unlike reaction time (power transformation), logarithm transformation was taken for efficiency to construct a valid data structure to conduct hypothetical testing. The domain of logarithm function takes positive values (greater than or equal to zero), and the calculated efficiency measures are negative values, negative efficiency measures were put into a logarithm function.

Mean transformed efficiency was significantly influenced by gender as shown in Table 2.7. Figure 2.5 shows the trend of efficiency in gender. The average (standard deviation) efficiency for female and male walkers were -0.0119 (0.0227) and -0.0185

(0.0186) respectively indicating female participants walked more effectively with less trajectory changes in forward movement angle than male walkers did.

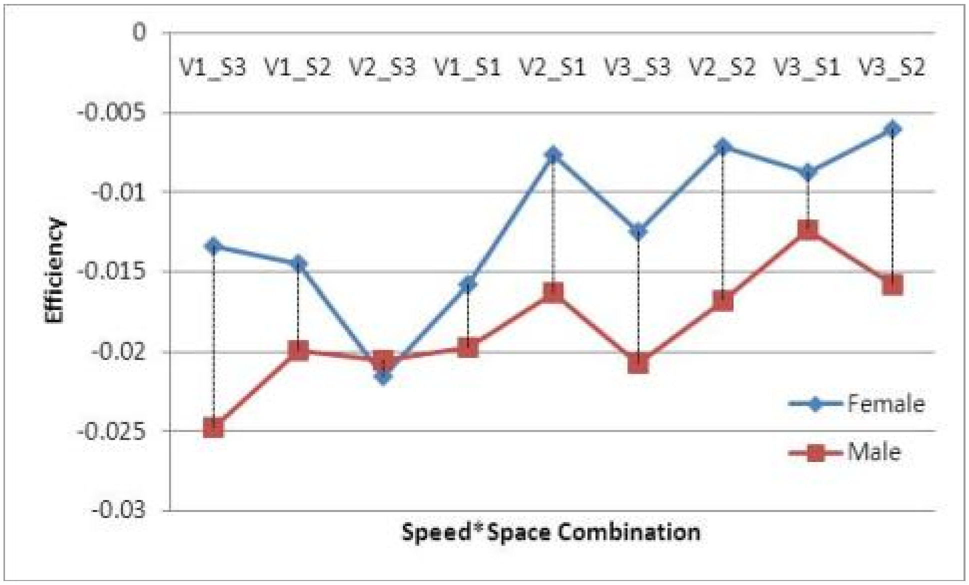

Figure 2.6 Task Efficiency Trends in Gender Based on Speed*Space Combination

No best situation (treatment combination of speed and space levels) for pedestrian walking was found as shown in Table 2.7. However, walking at fast speed with all space levels cases were better in mean transformed efficiency than slow speed class. For pedestrian space, multiple comparisons reported that space level B was better than level C in mean transformed efficiency.

Table 2.7 Fisher's Protected LSD Comparisons for Efficiency

Treatment combination (Speed_Space)	Mean	N	Groups		
V1_S3	-0.0190	60		A	
V1_S2	-0.0172	60		A	
V2_S3	-0.0210	60	B	A	
V1_S1	-0.0177	60	B	A	C
V2_S1	-0.0120	60	B	D	C
V3_S3	-0.0166	60	E	D	C
V2_S2	-0.0120	60	E	D	
V3_S1	-0.0106	60	E	D	
V3_S2	-0.0109	60	E		

2.7.3 Subjective Workload Measures

Subjective mental workload was also transformed using a natural logarithm function to conduct hypothetical testing under ANOVA assumptions.

Mean transformed workload was significantly influenced by gender as shown in Table 2.5. Figure 2.6 shows the trend of workload in gender. The average (standard deviation) workload for female and male pedestrians were 24.85 (13.97) and 20.17 (15.45) respectively indicating female participants experienced more workload while walking than male walkers did.

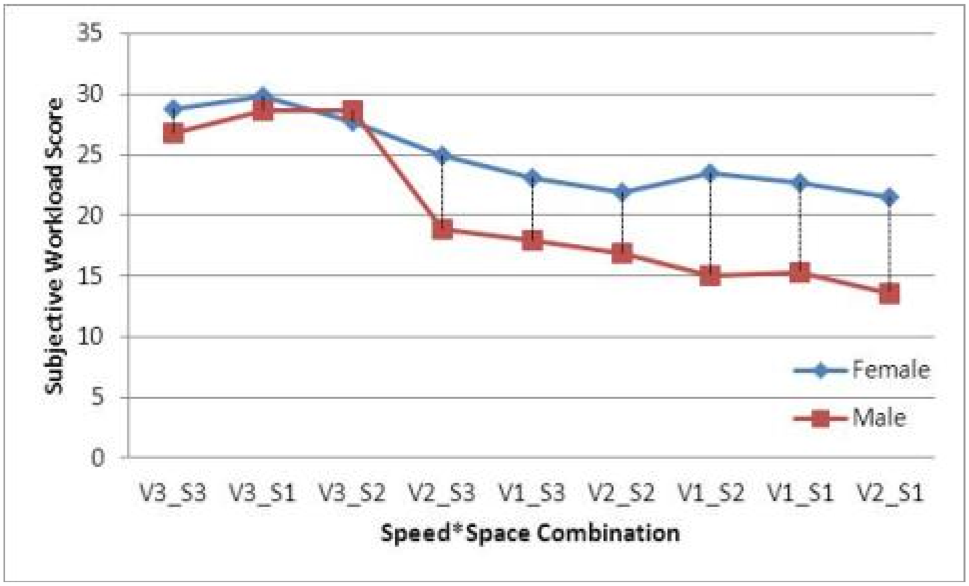

Figure 2.7 Subjective Workload Trends in Gender Based on Speed*Space Combination

No best treatment combination of speed and space levels that minimizes cognitive loading in walking tasks was found as shown in Table 2.8. However, multiple comparison results revealed that walking at fast speed with all space levels cases was worst with respect to mean transformed workload. Slow and normal speed levels were not significantly different with respect to mean workload score. There was no significant effect of pedestrian space on workload.

Table 2.8 Fisher's Protected LSD Comparisons for Workload

Treatment combination (Speed_Space)	Mean	N	Groups	
V3_S3	23.83607	60		A
V3_S1	23.47181	60		A
V3_S2	23.20343	60		A
V2_S3	18.24699	60		B
V1_S3	16.51716	60	C	B
V2_S2	15.83781	60	C	B
V1_S2	15.44368	60	C	B
V1_S1	15.23355	60	C	B
V2_S1	14.31489	60	C	

2.7.4 Relationship among Measures

To obtain correlation coefficients, "PROC CORR" was performed with a spearman option using SAS, since some of variables were not normally distributed and estimating exact probability distributions for all variables were not possible. Some weak but significant correlations were found between efficiency and all variables (workload, average observed walking speed, average acromion angle, average angular velocity of acromion angles, and gender), as well as between gender and most of the variables except angular velocity (Table 2.9). Average speed and average acromion angle are also negatively correlated each other. A strong correlation between average acromion angle and average angular velocity was found, since angular velocity is defined as changes between two consecutive acromion angles within a base measurement unit time, 0.016 seconds.

Table 2.9 Means, Standard Deviations, and Intercorrelations

			Intercorrelations						
Variable	Mean	SD	1	2	3	4	5	6	7
1. Reaction time (s)	0.5089	0.3924	1.00						
2. Efficiency	-0.0152	0.0210	-0.01	1.00					
3. Workload	22.5148	14.9034	0.05	**0.10**	1.00				
4. Average speed (m/s)	1.2480	0.2953	0.05	**0.37****	0.02	1.00			
5. Acromion angle (°)	0.8022	11.7270	0.02	**-0.10**	0.06	**-0.12***	1.00		
6. Angular velocity (°/s)	0.9746	6.5301	0.05	**-0.13***	0.05	-0.05	**0.87****	1.00	
7. Gender (female=1)	0.5000	0.5004	**-0.09**	**0.35****	**0.21****	**-0.15****	**0.13**	0.01	1.00

Note. N = 540.
Bold values indicate significant findings (p-value < 0.05), *p < 0.01., **p < 0.001
Gender = 0 if male; otherwise, female.

2.7.5 Regression Model

The bivariate correlations revealed three predictor variables were significantly related to average observed walking speed: efficiency ($r = 0.37$); average acromion angle ($r = -0.12$); and gender ($r = -0.15$) appeared in Table 2.9. All of these correlations were significant at p-value < 0.01, and all were in the predicted direction. The correlations between average speed and angular velocity and between average speed and reaction time, on the other hand, were nonsignificant with $r = 0.05$ and $r = 0.05$ respectively.

Multiple regression with stepwise method was performed to develop a regression model to predict mean walking speed (mm/s) taking into consideration of variables, such as reaction time, efficiency, workload and gender. Significance level of 0.15 for entering and removing variables was applied until no justifiable reason to enter or remove variables was found. Reaction time was removed by the entering variable criterion, and the obtained fitted equation is as follows (equation (2.2)).

$$\begin{aligned}\widehat{Speed} &= 617.7988 - 140.0523\ln(-efficiency) + 26.4371\ln(workload) \\ &\quad - 197.5814(gender) - 1.5691(acromionAngle) \\ &\quad \text{where}\begin{cases} gender = 0, \text{ if male} \\ gender = 1, \text{ if female} \end{cases}\end{aligned} \tag{2.2}$$

The predicted equation containing these four variables accounted for approximately 23% of observed variance in walking speed, $F(4,535) = 39.08$, $p < 0.0001$, adjusted $r^2 = 0.22$.

2.7.6 Cognitive Simulation Model Validation

For validating cognitive model performance, simulation experiments were conducted. Each simulation run of cognitive model in the study was treated as an actual experiment: the queueing network cognitive model was presented with ten stimuli occurring at random interarrival times ranging from five to sixty seconds and the simulation was replicated twenty times for representing twenty subjects.

Table 2.10 displays outcomes from cognitive model and comparisons with Model Human Processor (MHP) with respect to the predicted processing time at each subnetwork in the study and at each stage in MHP. Empirical study results from motion capture data is also reported in Table 2.10

Table 2.10 Information Processing Times (in seconds) Comparisons for the Simple Reaction Time Task

Processing Stage	Methods	Minimum	Mean	Maximum
Perceptual	Queueing N/W	0.050	0.098	0.196
	MHP	0.050	0.100	0.200
Cognitive	Queueing N/W	0.026	0.068	0.155
	MHP	0.025	0.070	0.170
Motor	Queueing N/W	0.030	0.069	0.148
	MHP	0.030	0.070	0.100
Total	Queueing N/W	0.106	0.235	0.499
	MHP	0.105	0.240	0.470
	Empirical	0.217	0.509	1.683
		95 % CI:	(0.475, 0.542)	

Pertaining to investigation of difference between MHP and queueing network cognitive model with respect to mean response time for both models, a single population mean t-tests was conducted and there was no significant difference between mean reaction times from both models ($t(19) = 2.52$, $p = 0.0208$). However, significant differences were found between queueing model and empirical study results as well as MHP and empirical study outcomes. As illustrated in Table 2.10, both results in mean response time did not fall within a 95% confidence interval of actual participants' response times from an empirical study.

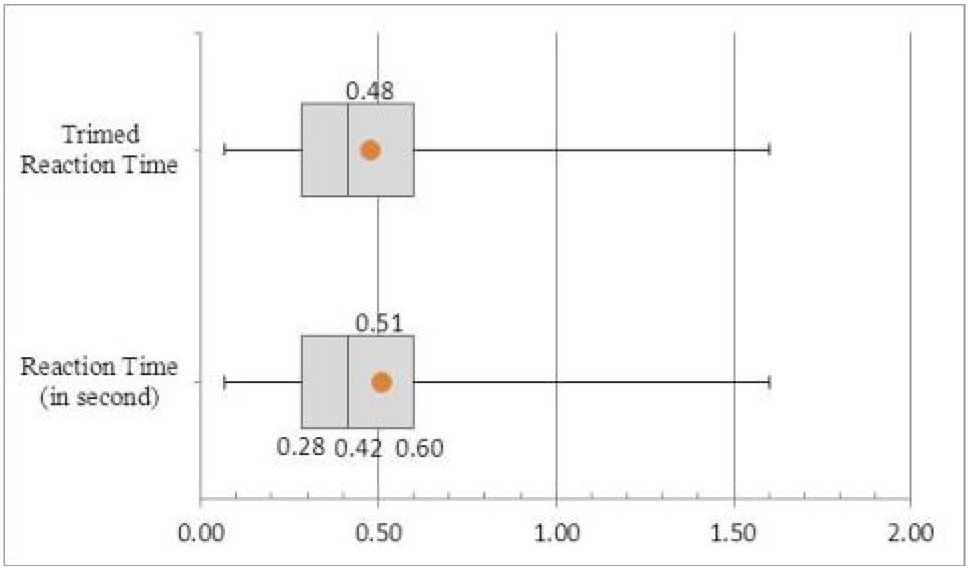

Figure 2.8 Box-and-Whisker Plot of Reaction Time (in seconds)

As shown in Figure 2.8, the distribution of participants' response times is skew to the right (with a skewness of 5.50) alluding that the data on response time contain numerous influential points that potentially impact on the central tendency of the data. The average response times from fast responding participants group (they responded immediately after they were given stimuli.), such as average of the data from minimum up to 25th percentile and 33rd percentile, were 0.2391 seconds and 0.2564 seconds respectively. This indirectly shows that as long as participants react immediately after the stimulus presentation, the predicted value of reaction time using the cognitive simulation model is consistent to the one observed.

2.8 Discussion

Motion capture cameras collect the data while communicating information regarding time and location with motion capture makers. There is no doubt the data collected with motion capture system may contain noise due to the fact that the system transmits the data through electro-magnetic signal. Moreover, motion capture system markers intervene in communications each other sometimes, so there is possibility of gathering unwanted or unintended data for these reasons. Data are necessary to be smoothed and cleaned beforehand.

Motion data regarding reaction time and efficiency for each motion capture markers in an x-y coordinate format were extracted from the motion capture software into each excel spreadsheet after taking position data smoothing. Butterworth smoothing algorithm in the motion capture software was applied abiding by recommended smoothing procedure to account for noise in the data (Marras et al., 1993; Allard et al., 1995).

If all the data on pedestrian behavior have been captured, what marker data do we need to select for identifying participant's forward movement? To address and resolve this issue, participants' walking trajectories were plotted and ran the correlation analysis with respect to forward movement angle for all markers. As described previously, markers were affixed on participants' top head, right-front head, right neck and both acromions. Data from both acromion makers were selected for analysis of the study since they explain the dimension of participants' body, they move together simultaneously maintaining constant distance between them. Especially the forward movement angle and vector can be easily obtained when a perpendicular line is drawn from a virtual line between two acromions. Forward movement angles were mostly orthogonal to a line between two acromions as illustrated in Figure 2.9.

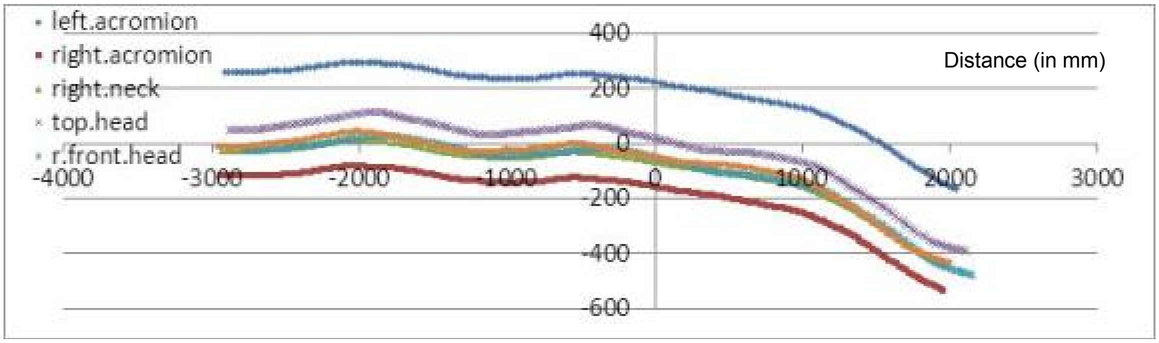

Figure 2.9 Trajectory Plot of Motion Capture Markers

Another reason for selecting acromion data was because it tells more about nonlinear forward movement of pedestrians, which is directly related to reaction time. As discussed in Chapter 4 and pedestrian literature, people are likely to change their waling speed rather than change their walking direction in angular degree. Also participants were asked to walk straight to the end of the experimental site taking a linear walking direction until stimuli are given to them. When measuring participants' response time, total time spent from the moment of stimulus presentation and until significant angular speed and angular acceleration were monitored on motion capture system was recorded. Figure 2.10 illustrates overall participants' average acromion angle (in degree), average angular velocity (in degree / millimeters) and average angular acceleration (in degree / milimeter^2). This shows participants do not prefer to change their walking direction (average change in angular degree is about 5°) and most of the tasks have been completed within an angular degree of 10 based on their microscopic forward movement angles. The overall pedestrian walking direction choices in degree are found in Figure 2.11.

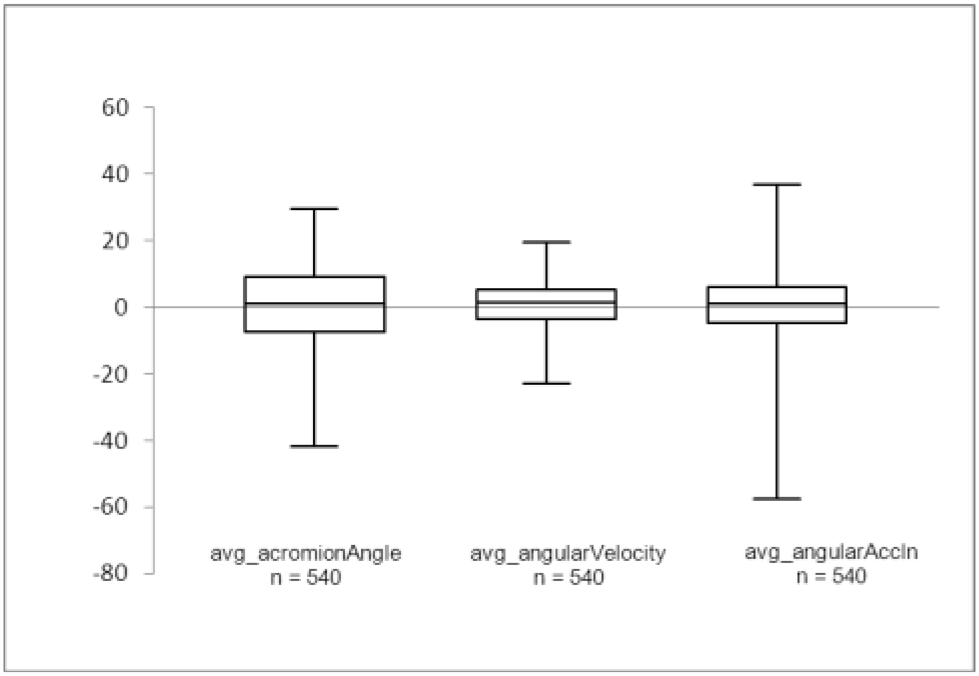

Figure 2.10 Box-and-Whisker Plots of Average Acromion Angle, Average Angular Velocity and Average Angular Acceleration for all Participants.

Note: They are nonlinear movement indices of pedestrian walking in the study.

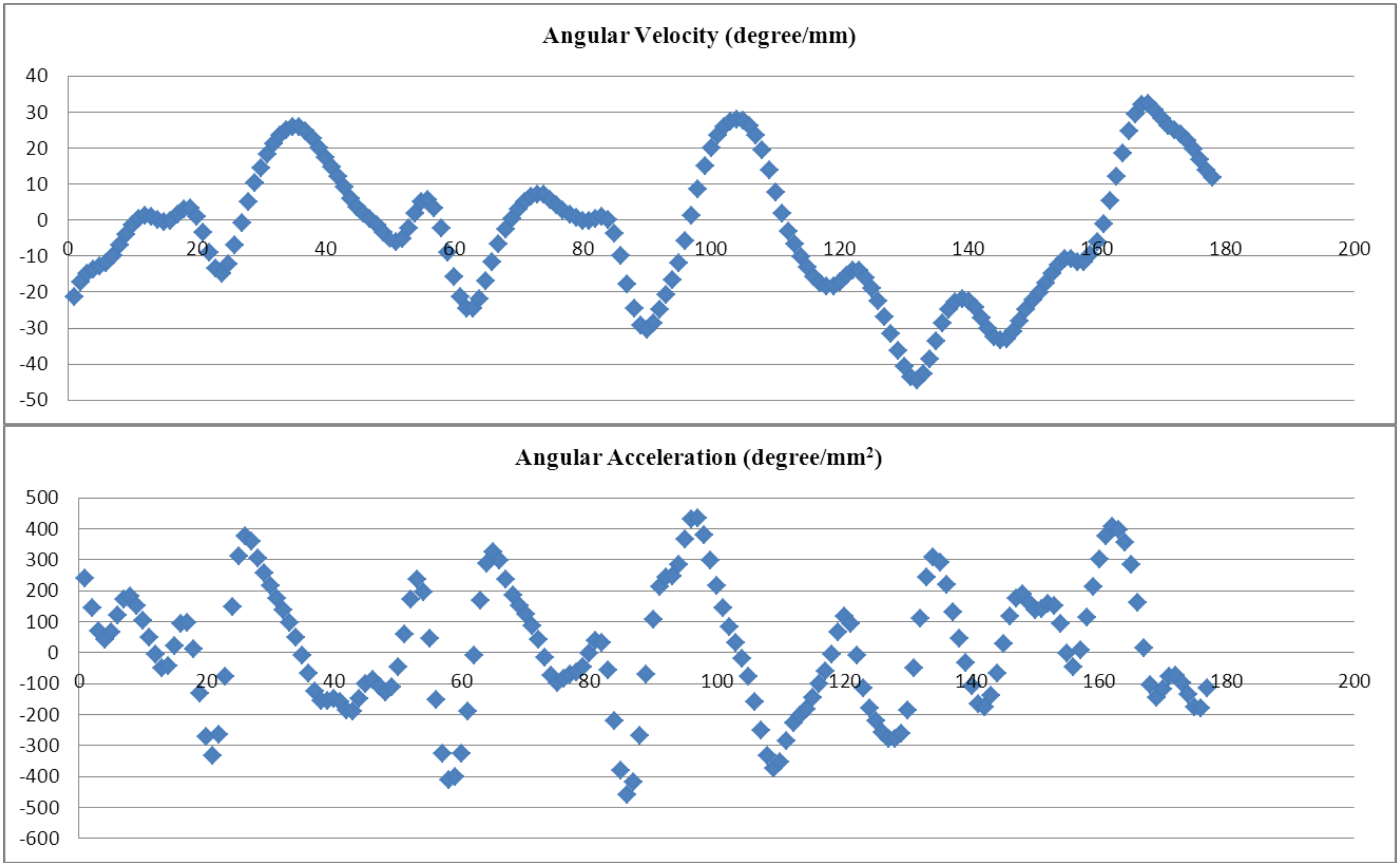

Figure 2.11 Observed Angular Velocity and Angular Acceleration

As noted in section 2.7, mean reaction time was not significantly affected by the combination of speed and space levels and even a single factor of space or asked speed. This can be interpreted as that there is no single level of speed or space that minimizes participants' reaction time. The interaction effect between each space and speed level was not significant that explains increasing space (speed) level does not have the same effect on the observed response time of pedestrians. No trend in mean response time as a function of space, either overall or in relation to the different speed levels either. At this point, the first research hypothesis was supported while parts of the second and the third hypotheses were not sustained. Then what was the reason that the contradictory would happen? This may be due to the fact that participants were not restricted to respond to the stimulus immediately after it is given to each participant. They were allowed to walk at their own judgment of each speed and to choose the direction as they believe it was appropriate to avoid possible collision. However, the reaction time averaged from its minimum up to 33rd percentile (0.2564 seconds) was consistent to the one predicted using queueing network model and MHP in terms of mean reaction time (e.g., $Q1_{\text{Reaction time}}$ = 0.2391 seconds as shown in Figure 2.8.).

The effect on mean efficiency measure and workload of space (or speed) do not depend on the level of speed (or space), which means F-tests on both interaction effects were not significant. The differences in mean efficiency and workload between the levels of space are not the same at all levels of speed. Therefore, the rest parts of hypotheses were supported by F-tests.

For efficiency measure, the effects of space and speed were significant. Unlike mean reaction time, variation due to gender was significant on mean efficiency. Female pedestrians have more linear trajectories than male walkers do. This can be interpreted as female participants tend to change their speed rather than change walking direction showing higher mean value of efficiency. There was no best speed and space combination that maximizes mean efficiency, but generally participants' efficiency measures were higher when they were asked at their slow speed for all levels of space. Therefore second and third hypotheses regarding mean efficiency were supported while forth hypothesis about efficiency was not held. As described previously, efficiency measure is a ratio of the difference between displacement and travel distance to displacement. This also can be thought of as an index of linear forward movement

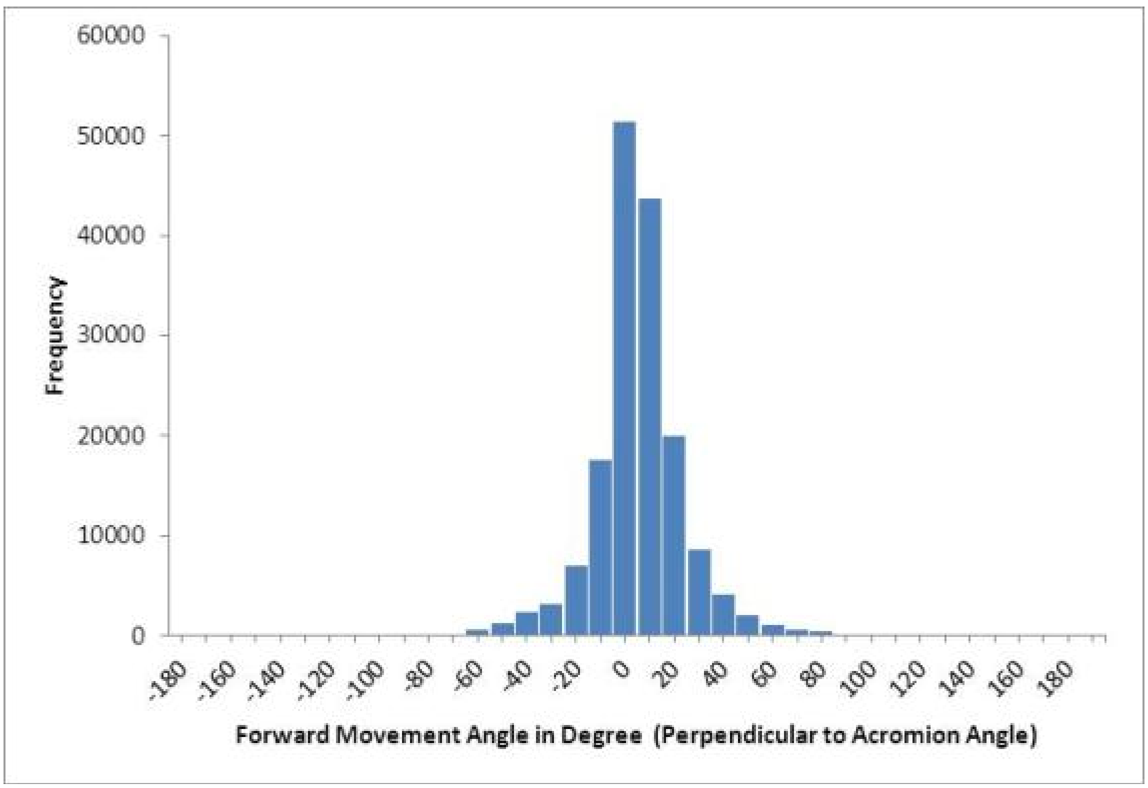

Figure 2.12 Histogram of Forward Movement Angle in Degree in Walking Direction Choice.

As shown in Figure 2.12, the central tendency of forward movement angle is almost zero with its mode of zero and the overall average efficiency is -0.0152, which indicates most participants took straight linear path while walking. Navigation tasks have been completed with the observed forward movement angle of less than 40 degrees as displayed in Figure 2.12. The recorded minimum and maximum values of efficiency were -0.2761 and -0.0007 respectively, and they were observed in forward movement angle range between -10° and +10°. This proves that efficiency is an appropriate measure for linear forward movement that minimizes travel time and use of space as well as mental workload. Similar, consistent tendency of walking direction path choice was found in literature as shown in Figure 2.13. Path choice alternatives 5, 6, 7, 16, 17, 18, 27, 28, and 29 in Figure 2.13 regarding forward movement angle range between -10° and +10° as well.

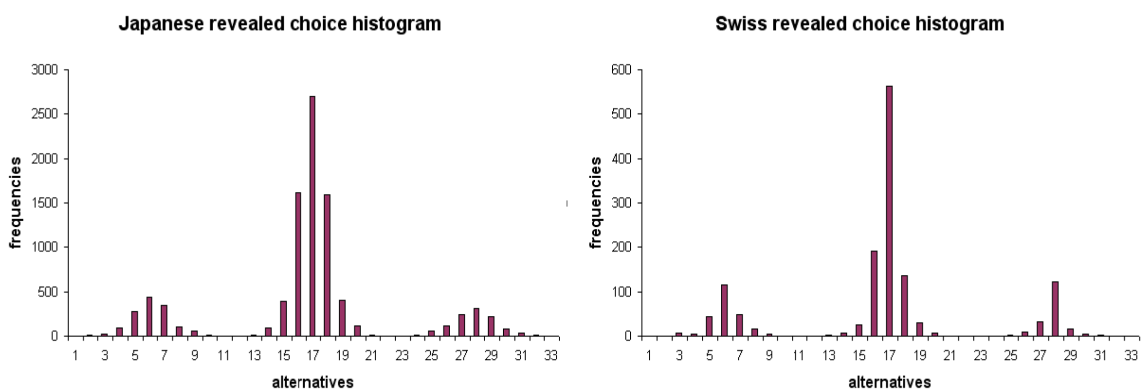

Figure 2.13 Histograms of Pedestrian Path Choice in the Literature (Robin et al., 2009)

Note: The study was inspired and motivated by this pedestrian path choice model proposed by Robin et al. (2009) and Antonini et al. (2006). The numeral numbers on x-axes (i.e., path choice alternatives) have been applied to one of study protocols in the study as illustrated in Figure 2.1 and Figure 2.3.

2.9 Conclusion and Future Work

The overall objective of this study was to model and construct cognitive information processes of visual search in pedestrian navigation. For detailed measurement of pedestrian movement at a cognitive information processing level as employed in ACT-R (Anderson et al., 1997), a motion capture system was utilized. The motion capture system collected pedestrian movement every 0.015 seconds. Based on collected location information about affixed motion capture markers, instantaneous speed, acromion angle, and its angular velocity and acceleration were computed for further analysis.

Effects of pedestrian space and speed on reaction time, efficiency and mental workload were tested. Changes in levels of space and speed did not significantly affect mean reaction time since participants' were free to choose their own moment of reaction as long as they not collide with obstruction. This was compared with predicted reaction time to validate the mode performance for further use and development of cognitive information processing model discussed in the next chapter. It has been found that there is no significant different difference between empirical study results and predicted one with respect to mean reaction time. Unlike reaction time, efficiency and mental workload measures were affected by changes in levels of space and speed.

Since queueing network cognitive model enables researchers to investigate and understand the architecture of human information processing, as well as to utilize tools for estimating the average reaction time and mental workload, one can obtain credible predicted values of reaction time (sometimes task completion time) and mental workload in a very short period of time as long as he/she has a basic understanding about elementary queueing systems and GOMS style task descriptions.

However, QN-MHP model assumed that interarrival and entity (i.e., stimulus) processing times are exponentially distributed. As one can notice this may be very rare cases to come up with in real life and sometimes just mean and variance of entity processing time can be obtained without having perfect information about service time distribution. To overcome and resolve this issue, another cognitive information processing model based on queueing network system with general service time distribution is considered in the next chapter so that the credible predicted reaction time can be obtained with the first moment of service time distribution.

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CHAPTER III

STOCHASTIC MODELING OF COGNITIVE INFORMATION PROCESSING USING APPROXIMATED QUEUEING SYSTEMS

3.1 Abstract

This study investigates the configuration of cognitive information process using task description-based queueing network to estimate the reaction time for a given task. The reaction time is defined as the delay between exterior stimulus presentation and reflection initiation. The study of reaction time helps to better understand the possible structure of a mental processing system that encompasses various stimuli, information processing units and dynamic responses. Approximations for the system size of queueing systems are presented to stochastically model the mental structure and to examine reaction time. The approximation algorithm provides the system size distributions without taking transformation that includes a finite capacity system (M/G/c/c) and an infinite queue (M/G/c). To represent cognitive structure using the proposed queueing system in this study, each server node is identified by neuroscience research findings, GOMS (goals, operators, methods and selection rules) procedure, and the routes which customers can take to finish service. Customer sojourn time is used to compute reaction time. The effectiveness and efficiency of the approximation method and estimated reaction time are discussed by comparing empirical results with simulated results for the mean reaction time.

The approximation showed high precisions when the traffic intensity were low, medium and medium-high while its performance got poorer as a traffic intensity is high (e.g., 0.95 or higher). There was no significant difference between empirical study results and the proposed model with respect to mean reaction time. Future work pertaining to improving the performance of the model and incorporating the model into the planned pedestrian simulator is discussed.

Keywords: Cognitive process, GOMS, human information processing, M/G/c queue, approximation, system size distribution

3.2 Introduction

Understanding the human cognitive structure and the required time to process information is a key issue in modeling human behavior with multiple agents that represent human operators. This issue has been studied in both cognitive science and artificial intelligence arenas for decades using knowledge-based and performance-based representations. Cognitive modeling approaches with knowledge-based representation can be applied to resolve this issue appropriately. Because the GOMS family models are versatile to describe knowledge-based procedural task that requires human operators maximizing task performance (Card et al., 1983), knowledge-based task description approach using GOMS has been used in transportation research (Wu et al., 2008). Queueing theory is one of the frequently used tools to construct a performance-based model, such as telecommunications systems (Erlang, 1909; Cooper, 1981), or production and transportation systems (Gross et al., 2008). Recently, it has been applied to model human cognitive performance (Liu, 1996; Feyen & Liu, 2001).

Previous research on cognitive information processing using queueing systems relied on assumptions to represent human information processing system (Baron et al., 1990). First, the method to process information was confined to serial processing for all stages of information processes, such as perceptive, cognitive and motor processes. This assumption may not be appropriate, because peripheral perceptive and motor processes continue in parallel and only a cognitive stage is processed in serial based on neuroscience researches (Pashler, 1994; Sigman & Dehaene, 2008). Secondly, a single server system was applied to structure the information process. Under this assumption, it may not be possible to represent multiple task situations due to its architectural limitation. Third, the methodology assumed the capacity of information processing unit is infinite. This also may violate the well-known theory of limits on human capacity for processing information (i.e., seven plus or minus two) (Miller, 1956).

The study endeavored to encompass both a performance-based method (queueing systems) and a knowledge-based approach (GOMS) for modeling stochastic cognitive information process and obtaining the estimated information processing time, while relaxing assumptions in literature that models cognitive information process using queueing systems.

A queueing system provides an appropriate methodology for the analysis of waiting phenomena such as average waiting time, average sojourn time, and average number of customers in the system. There has been no exact solution for M/G/c queueing systems, though a number of techniques have been presented for the M/G/1 model to obtain exact solution, such as ‘imbedded Markov chain method’, ‘supplementary variable technique’, etc. (Tijms, 1994; Gross et al., 2008). For this reason, approximation approaches have been attempted to provide quick-and-dirty solutions (Cruz et al., 2005; Cruz & Smith., 2007). Boot and Tijms (1999) discussed an impatient customer problem, in which the system loses a customer if the customer is not served within a certain period of time. Kimura (1996) presented system size distribution using a solution of M/M/c system, which yields a fairly precise solution for a finite system. In this research, an analytic approximation algorithm was developed to obtain the steady state solution for the system size of the M/G/c queueing system without taking transformations. The steady state solution was derived by using a Markovian service time model approach and system balance equation based on types of offered load on waiting space. Therefore, this study aimed to provide a simple and reliable solution that reduces computation time and memory space.

Human factors researchers have used various mathematical approaches to model specific types of human performance tasks. For instance, knowledge-based approaches replace the several individual algorithmic functions specific to each step in a task network model. Whereas task networks and mathematical approaches focus on the activity being performed, knowledge-based approaches tend to focus on the process used by the human system to select and generate the desired activity. Knowledge-based approaches include ACT-R (Anderson & Lebiere, 1998), EPIC (Kieras & Meyer, 1997), MIDAS (Laughery & Corker, 1997), the GOMS family of models (John & Kieras, 1996), and the Model Human Processor (Card et al., 1983). These approaches have considerable strength in modeling the behaviors that a human might exhibit when interacting with a system. However, neither the knowledge-based nor task network approaches are based on mathematical theories amenable to producing time-and-capacity-based performance measures (Baron et al., 1990). The study efforts are focused on integrating the advantageous factors in queueing network and knowledge-based task modeling to increase the effects of modeling and computation.

Since the mathematical calculations for performance measures in queueing systems are often intractable, approximation algorithms for queueing systems was aimed. This study presented a transform-free approximation for the system size of M/G/c queueing systems. When the number of customers in the system is less than or equal to the number of servers, its distribution was derived utilizing the Markovian service time model and a new parameter. To obtain the probability of the number of customer being greater than the number of servers, a queue was regarded as a set of separate waiting spaces rather than the whole entire queue, and types of load on each waiting space were classified based on the number of occupied waiting spaces in the system. The efficiency and effectiveness of the approximation were investigated with simulation experiments. To apply the developed approximate formulation for queueing system to the task description-based cognitive network model, the network expansion method from a single queueing system was also discussed. Finally, the estimated values of minimum and average reaction times and related workload were presented.

3.3 System Size Distribution

The arrival of customers follows a Poisson process with an arrival rate of λ (i.e., the interarrival time is exponentially distributed). The service time (S) of each server has a general distribution, G, with an average service time of $E[S] = 1/\mu$. The system contains c identical and independent servers. Also, the interarrival time and service time are assumed to be statistically independent. It is assumed that the system capacity is infinite and the system satisfies steady-state conditions ($\lambda < c\mu$). If there is a customer in a queue, a server cannot be idle and the customer will be served as soon as any service finishes. The service policy of this system is based on first-come-first-served (FCFS). The system size distribution is derived for the number of customer in the system being less than or equal to c and greater than c respectively

3.3.1 System Size ≤ c

Suppose that N is the number of customers in system under steady state in M/M/c system, then $\Pr(N=n)=P_n(M)$ is defined as the equation below:

$$P_n(M)=\begin{cases}(\lambda/\mu)^n P_0(M), & (0\le n\le c-1)\\ C(c,c\rho)(1-\rho)\rho^{n-c}, & (n\ge c)\end{cases}$$
$$\text{where: } \rho=\frac{\lambda}{c\mu},\ C(c,c\rho)=\frac{(\lambda/\mu)^c}{c!}\frac{1}{1-\rho}P_0(M) \text{ and} \tag{3.1}$$
$$P_0(M)=\left(\sum_{n=0}^{c-1}\frac{(\lambda/\mu)^n}{n!}+\frac{(\lambda/\mu)^c}{c!(1-\rho)}\right)^{-1}$$

$C(c,c\rho)$ can be thought of as the probability of all servers being busy (or probability of waiting for all arrival customers based on PASTA (Poisson Arrival Sees Time Average)) (Wolff, 1982, 1989).

Kimura (1996) presented the solution for M/G/c model directly using M/M/c system solution when the number of customers in system is less than c. A fairly good precision of approximation for the loss system with no extra waiting space was presented. Since the M/G/c system has similar characteristics to an M/M/c system if all servers are not busy simultaneously, the M/M/c system was used as the prototype of approximation for the system size distribution. To approximate the M/G/c system size distribution, a new parameter, v ($0< v <1$), is assigned to equation (3.1) substituting it for ρ. Suppose

$P_n(G)$ is the probability of *n* customers in M/G/c system, then the equation can be replaced as below:

$$P_n(G) = \begin{cases} (\lambda / \mu)^n P_0(M), & (0 \le n \le c-1) \\ C(c, c\rho)(1-\nu)\nu^{n-c}, & (n = c) \end{cases} \tag{3.2}$$

Similar approximation methodologies to Equation (3.2) have been presented (Miyazawa, 1986; Tijms, 1994). In many cases, researchers have used parameter ν to describe the ratio of busy period as a measure of load in the multi-server systems (Tijms, 1994). To obtain *v*, Little's law (Little, 1961) and the moment matching method are applied. Little's law is applied in this study since it is applicable for any system irrespective of the number of servers, service policy and service discipline. Little's law is defined as $L = \lambda W$, where L is average number of customer in the system and W is average time in system. Then, Little's equations for M/M/c and M/G/c can be described as $L_{q,M/M/c} = \lambda W_{q,M/M/c}$ and $L_{q,M/G/c} = \lambda W_{q,M/G/c}$. After arranging equations with respect to λ, and perform a moment matching, the following asymptotic relationship is obtained (Kimura, 1996):

$$\frac{\rho}{1-\rho} W_{q,M/G/c} \simeq \frac{\nu}{1-\nu} W_{q,M/M/c} \tag{3.3}$$

Let R be the ratio of both average waiting times:

$$R \equiv \frac{W_{q,M/G/c}}{W_{q,M/M/c}} \tag{3.4}$$

Then, the parameter, *v*, in equation (3.2) can be derived using equations (3.3) and (3.4) :

$$\nu = \frac{\rho R}{1-\rho+\rho R} \tag{3.5}$$

Kimura (1996) approximates R limiting ρ to zero, $\lim_{\rho\to 0} R = c \cdot E[T_1^+] \cdot \frac{1}{E[S]}$ where $E[T_1^+]$ is the average minimum remaining service time at any time of moment, and it is written $E[T_1^+] = E[\min\{S_1^+, S_2^+, \cdots, S_c^+\} = \int_0^\infty (1 - G_+(t))^c dt$ implying S_k^+ and G_+, which are the remaining service time of server k and the distribution function of remaining service time respectively. Wang and Wolff (1998) showed $E[T_1^+]$ can be approximated, and noted it yields a good empirical result such that $E[T_1^+] \approx \frac{E[S] + 3E[S^+]}{4c}$. Hence, R is approximately derived as following equation:

$$\lim_{\rho\to 0} R = \frac{1}{4}\left\{1 + \frac{3E[S^2]}{2E^2[S]}\right\} \tag{3.6}$$

Now, v can be obtained using equation (3.6) plugging it into equation (3.2) to derive $P_0(G)$.

$$P_c(G) = \frac{(\lambda/\mu)^c}{n!} \cdot \frac{1-\nu}{1-\rho} \cdot P_0(M) \tag{3.7}$$

Putting $P_c(G) \equiv P_c$ for simplicity, system size distribution of ($n > c$) is derived in the next section.

3.3.2 System Size > c

Arriving customers wait in the queue when the number of customer in the system is greater than or equal to the number of servers. In this study, the queue is regarded as a set of separate waiting spaces rather than the entire queue as a whole as illustrated in Figure 3.1. Each customer waits in the waiting space for the minimum remaining service time of customers being served, and shifts forward toward the server by one waiting space whenever a busy server completes the service.

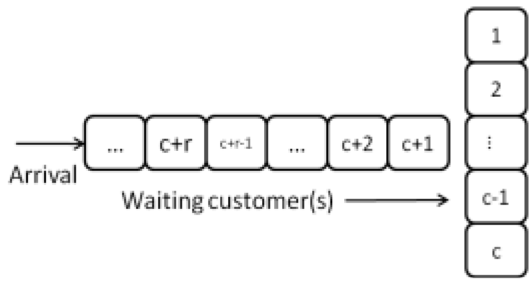

Figure 3.1 System of Interest

Let R_{c+r} be the r^{th} waiting space. The phenomenon R_{c+r} is busy, which implies that a customer occupies the r^{th} waiting space. At any point of time, the probability of the r^{th} waiting space being busy is equivalent to the probability that there are at least $(c + r)$ customers in the system under steady state condition. Let Q_{c+r} be the utilization (offered load per unit-time) of the r^{th} waiting space. According to the number of customers in the system (n), the intensity of the offered load differs. Types of offered load can be classified into three types based on the system state at arbitrary arrival epoch: (1) $n \leq c+r-2$, no load on R_{c+r}; (2) $n=c+r-1$, the arriving customer waits in the system for the minimum remaining service time of customers being served; and (3) $n \geq c+r$, the arriving customer waits for the minimum of new service time at server c and the remaining service times of other busy servers. Then the average load on r^{th} waiting space (R_{c+r}, $r \geq 1$) is:

$$\begin{aligned} Q_{c+r} &= P_{c+r} + P_{c+r+1} + P_{c+r+2} + \cdots \\ &= \lambda(P_0 + P_1 + \cdots + P_{c+r-2}) \cdot 0 + \lambda P_{c+r-1} E[T_1^+] + \lambda(P_{c+r} + P_{c+r+1} + \cdots) E[T_2^+] \end{aligned} \tag{3.8}$$

where $T_2^+ = \min\{S, S_1^+, S_2^+, \cdots, S_{c-1}^+\}$, which is the minimum of new service time at server c (i.e., S) and the remaining service times of busy servers ($S_1^+, S_2^+, \cdots, S_{c-1}^+$). Since $P_{c+r} = Q_{c+r} - Q_{c+r-1}$, the system size distribution (P_{c+r}, $r \geq 1$) and probability of r^{th} waiting space being occupied (Q_{c+r}, $r \geq 1$) can be obtained by solving the balance equation in equation (3.8) recursively.

$$Q_{c+r} = \frac{\lambda E[T_1^+]}{1-\lambda E[T_2^+]} P_{c+r-1} \tag{3.9}$$

$$P_{c+r} = \frac{\lambda E[T_1^+]}{1-\lambda E[T_2^+]+\lambda E[T_1^+]} P_{c+r-1} = \left(\frac{\lambda E[T_1^+]}{1-\lambda E[T_2^+]+\lambda E[T_1^+]}\right)^r P_c \tag{3.10}$$

Each state probability contains two types of average service time, $E[T_1^+]$ and $E[T_2^+]$. The former was obtained in step-1, and the latter is derived as follows:

$$\begin{aligned}
&E[\min\{S, n^{th}\text{smallest of}\,(S_1^+, S_2^+, \cdots, S_{c-1}^+)\}] \\
&= \int_0^\infty \Pr(S > t)\cdot \Pr\{n^{th}\text{smallest of}\,(S_1^+, S_2^+, \cdots, S_{c-1}^+) > t\}dt \\
&= \int_0^\infty E[S]\sum_{i=0}^{n-1}\binom{c-1}{i} G_+^i(t)(1-G_+(t))^{c-1-i} g_+(t)dt \\
&= E[S]\sum_{i=0}^{n-1}\binom{c-1}{i}\int_0^1 z^i(1-z)^{c-1-i}dz \\
&= E[S]\sum_{i=0}^{n-1}\binom{c-1}{i}\frac{i!(c-1-i)!}{c!} = E[S]\frac{n}{c}
\end{aligned} \tag{3.11}$$

The previous integration equation in equation (3.11) is derived by writing $G_+(t) = z$ and substituting $0 < G_+(t) = z < 1$ for integration interval, $(0 < t < \infty)$ to use beta probability distribution. Then, $E[T_2^+]$ is obtained by plugging n=1 in equation (3.11):

$$E[T_2^+] = \frac{1}{c}E[S] \tag{3.12}$$

The transform-free system size distribution for the M/G/c queueing system can be obtained arranging all the derivation results as follows:

$$P_n(G) = \begin{cases} \dfrac{(\lambda/\mu)^n}{n!} P_0(M), & (0 \le n \le c-1) \\ \dfrac{(\lambda/\mu)^c}{c!} \dfrac{1-\nu}{1-\rho} P_0(M), & (n = c) \\ \dfrac{(\lambda/\mu)^c}{c!} \dfrac{1-\nu}{1-\rho} \left(\dfrac{c\lambda E[S]}{c(c+1)-\lambda E[S]} \right)^{n-c} \cdot P_0(M), & (n > c,\ r \ge 1) \end{cases} \tag{3.13}$$

where $\rho = \dfrac{\lambda}{c\mu}$ and $P_0(M) = \left(\sum_{n=0}^{c-1} \dfrac{(\lambda/\mu)^n}{n!} + \dfrac{(\lambda/\mu)^c}{c!(1-\rho)} \right)^{-1}$.

As described in equation (3.13), the approximation for the system size distribution of infinite queues has been developed. The approximation for finite systems (M/G/c/K) can be obtained by truncating and normalizing $P_0(M)$, and replacing it with the following term:

$$P_0^{(K)} = \left(\sum_{n=0}^{c-1} \frac{(\lambda/\mu)^n}{n!} + \frac{(\lambda/\mu)^c}{c!} \frac{1-\rho\nu^r}{1-\rho} \right)^{-1} \tag{3.14}$$

where $K = c + r$.

3.4 Expansion of Queueing Systems to Cognitive Process Networks

The expansion method adds a retrial queue (node R) for each finite queue (node) in the network to register blocked customers, also known as overflows. When the customer is blocked (Figure 3.2b) since the next queue is at its full capacity, a retrial node will hold and act as a service station to the blocked customer. If P_c is the blocking probability of node 2, then P_c shall be the probability of customer going through node R preceding the capacitated node. The blocked customer shall proceed from node R to node 2 with probability of $(1 - P_c^{'})$, or remain at the retrial node with probability $P_c^{'}$ if node 2 is still full. However, if node 2 is not saturated (Figure 3.2a), customers proceed to its queue with probability of $(1 – P_c)$.

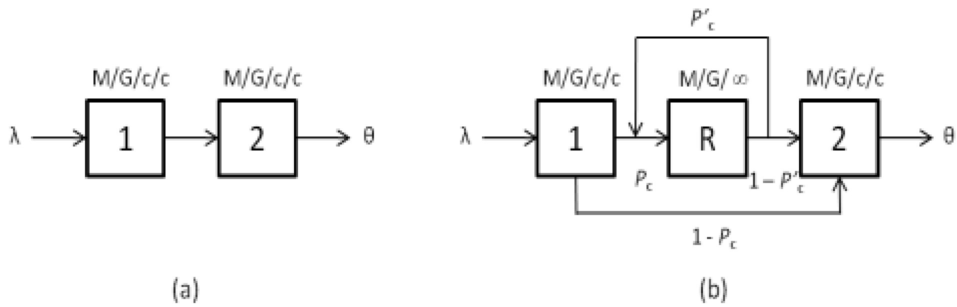

Figure 3.2 M/G/c/c Queues Expansion

After incurring a delay at the retrial node (node R), an overflow customer proceeds to the capacitated server node from which it was previously rejected. If the queue is still full, it incurs another delay. To appropriately represent this process, the artificial node has a feedback arc to account for these attempts.

Combining the approximations and network expansion methodology developed previously, the cognitive process network is constructed. For a couple of appropriate reasons described previously, the capacity of each server node is reconstructed and confined to a finite system. It is generally believed and accepted that there is limitation on human information processing capacity of 7 ± 2 (Miller, 1956). Therefore, the system of interest in this study is targeted to M/G/c/c, where $c = 7 \pm 2$. Additionally, the reversed process of the M/G/c/c state dependent queue is of the same type as the forward process, with customers arriving by a Poisson process with rate of λ, having workload distributed according to G and with the state representing the ordered residual workloads of customers presently in the system (i.e., the departure process, for both customers completing service and those that are lost, is a Poisson process as well). The system size distribution of the target queue is as follows:

$$P_n(G) = \begin{cases} \dfrac{(\lambda/\mu)^n}{n!} P_0^{(c)}, & (0 \le n \le c-1) \\ \dfrac{(\lambda/\mu)^c}{c!} \dfrac{1-\nu}{1-\rho} P_0^{(c)}, & (n = c) \end{cases} \tag{3.15}$$

$$\text{where } \rho = \frac{\lambda}{c\mu} \text{ and } P_0^{(c)} = \left(\sum_{n=0}^{c} \frac{(\lambda/\mu)^n}{n!} \right)^{-1}.$$

Some appropriate definitions and assumptions are required to construct the mental network model with generalized queueing systems developed previously. The basic components of the system encompasses node, arc, stochastic processes for interarrival time and service time, arrival rate, service rate, and service discipline. Liu (1996) proposed a simple M/M/1 queueing network model of elementary mental processes that includes basic queueing network components matching mental processing system to his system of interest. Even though this study takes into consideration a generalized model with general service time processes, multi-servers at each server station, and closed form of equilibrium solution, the basic definition of system components is adopted by his work as long as the assumption is consistent to the model of this study. Each node (i), representing an information processing unit, provides a distinct type of information processing service to the customers (stimuli) and has been identified by Feyen (2002). A node represents a server, and the total number of server nodes (S) for the system must be determined beforehand. Two types of nodes are present in the network system; input and internal nodes. Input nodes receive customers from outside of the network, and internal nodes receive customers within the network either from inside of the sub-network or other sub-networks assuming that input nodes may or may not provide service to customers immediately. Each arc indicates the direction (i.e., a route) from a server to the next server. The time between two consecutive nodes is assumed to be negligible. Unlike routing time between two consecutive nodes, if a server must perform a complicated service, it takes time for a server to complete the service (see Figure 3.3 for server processing times in each sub-network.). There are two types of arrival rates: (1) Mean arrival rate (γ_i) from outside of the network to node i; and (2) the total arrival rate (λ_i) into node i from both outside the network and other nodes. The probability (P_{ij}) that a customer visits node j immediately after departing from node i, where $i \neq j$, i=1,2,⋯,S and j=0,1,⋯,S with P_{i0} representing the probability of customer's leaving the network immediately after visiting node i. Finally, μ_i indicates the mean service rate for each channel of node i. A server (node) that simply routes information to another server is assumed to require no processing time.

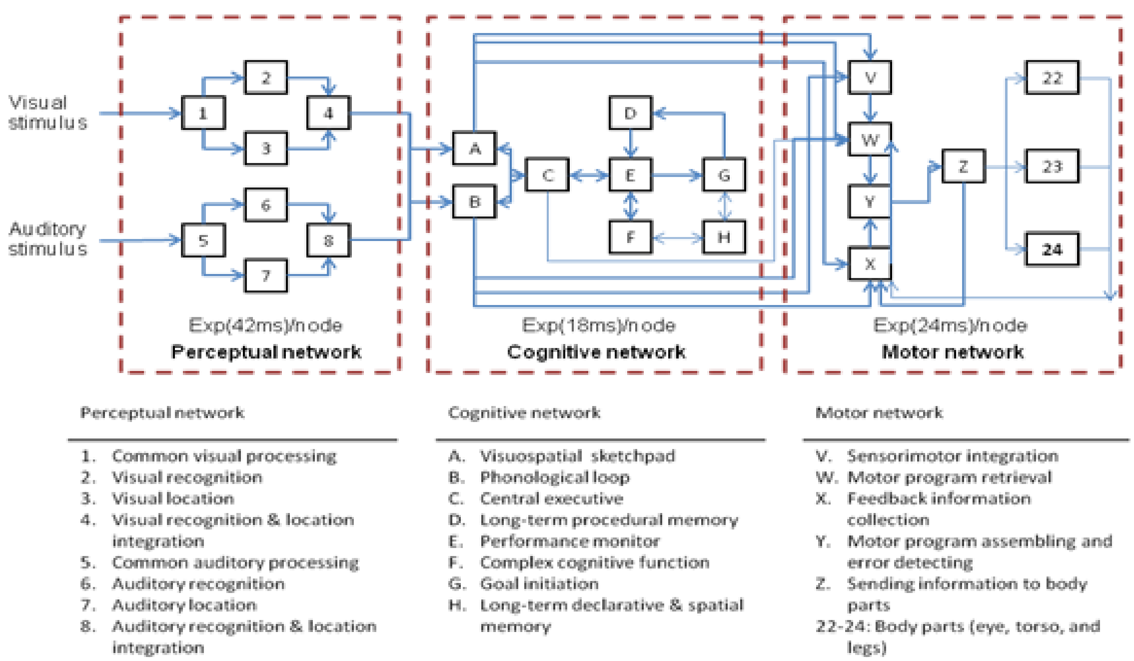

Figure 3.3 Cognitive Information Processing Network (modified from Liu et al., 2006)

To represent mental process into perceptual, cognitive, and motor sub-networks, Liu and his colleagues (2006) decompose the entire network using Model Human Processor (MHP) (Card et al. 1983) as illustrated in Figure 3.3. They reviewed neuroscience research findings to identify relevant areas of the brain that might represent common cortical fields activated during the performance of a given task and to determine the primary connections between these fields. In this study, three additional nodes for motor sub-network are included that represent the forehead, chest, and legs to actuate appropriate body reactions to input stimuli. The nodes are represented in Figure 3.3 as nodes 22, 23, and 24.

To estimate the average reaction time, the summation of each service time from the selected nodes is calculated. The selection of nodes is identified through cognitive task analysis, which details the specific procedures required for the task. Feyen and Liu (2001) organized the task procedure and matched each step to the appropriate node in the network using GOMS (Card et al., 1983). The task procedure encompassed the 24 operators including motor, perceptual, cognitive, memory access, and procedure flow operators (Liu et al., 2006). A motor operator has functions such as reach to target, move object to target, apply pressure to object, release object, and delay movement for a specified time. A perceptual processing operator includes glance at a target, watch target until stimulus data, compare stimulus data to cognitive function, verify stimulus data, and trigger action given stimulus. A complex cognitive operator embraces select search target, decide, compute, and time check. A memory access operator contains recall information from working memory, retain entity in working memory, retrieve information from long term memory, and forget all retained entities. A procedural flow operator involves accomplish goal, report goal accomplish, and go to step number.

Procedural flow operators are implemented in the procedural list server. Motor, perceptual processing, complex cognitive, and memory access operators are defined and executed at the nodes Z, C, F, and C respectively as illustrated in Figure 3.3. Since the queueing network has a task a independent cognitive structure, to model any particular task (e.g., visual search task), the specific procedure that is needed to perform the task (i.e., task procedure) is described by the GOMS style hierarchical task description (Table 3.1) that is used to compute the cognitive processing time for visual search task as indicated in Figure 3.3. As an example, the task of a pedestrian's visual obstacle detection is given. The objective of the visual search is to find an appropriate path that a pedestrian can take to avoid probable collision while navigating. A pedestrian is required to identify possible obstructions in the pedestrian facility.

Table 3.1 GOMS Style Task Description of the Visual Search in Pedestrian Navigation

GOAL: Do visual path choice task

Method for GOAL: Do visual path choice task

- Step 1: WATCH for <sub-destination> in <facility>
- Step 2: RETAIN <sub-destination>
- Step 3: Walk on <path> in <facility segment> on <foot>
- Step 4: DECIDE: If <sub-destination> is <the end of agenda>, then move step 5; Else go to step
- Step 5: CEASE // task completed

Method for GOAL: Walk on <path> in <facility segment> on <foot>

- Step 1: DECIDE: If location of <path> in memory, then move to step 3; Else go to step 2
- Step 2: Visual search for <location> of <path> in <facility segment>
- Step 3: REACH <path> in <facility segment> on <foot>
- Step 4: RETURN with goal accomplished

Method for GOAL: Visual search for <path> in <facility segment>

- Step 1: RECALL <sub-destination> from <working memory> as <target sub-destination>
- Step 2: WATCH for <path direction> in <facility segment>
- Step 3: COMPARE: <path direction> with <target sub-destination>
- Step 4: DECIDE: If match, then go to step 5; Else move to step 2
- Step 5: RETAIN <location> of <path direction>
- Step 6: RETURN with goal accomplished

3.5 Execution and Validation of the Model

Numerical analysis on the average number of customer in system was conducted by changing service time distribution, number of servers, and traffic intensity (ρ). The arrival rate was fixed (λ) for simplicity, and service time distributions were exponential, Erlang-3, Erlang-8 and deterministic. The number of servers for the experiment was three and five with traffic intensities of 0.1, 0.3, 0.5, 0.7, 0.9 and 0.95 respectively. To compare the precision of an approximation, percent relative error was used.

Table 3.2 Average Number of Customers for M/M/c Systems

c	*ρ*	Exact	Approx	Error (%)
3	0.1	0.30	0.30	0.00
	0.3	0.93	0.93	0.00
	0.5	1.74	1.74	0.00
	0.7	3.25	3.25	0.00
	0.9	10.05	10.05	0.00
	0.95	20.08	20.08	0.00
5	0.1	0.50	0.50	0.00
	0.3	1.51	1.51	0.00
	0.5	2.63	2.63	0.00
	0.7	4.38	4.38	0.00
	0.9	11.36	11.36	0.00
	0.95	21.43	21.43	0.00

Note. Error = (|Exact – Approximation| / Exact) * 100 (%)

Table 3.3 Average Number of Customers for M/E_3/c Systems

c	*ρ*	Simulation	Approx.	Error (%)
3	0.1	0.30	0.30	0.00
	0.3	0.92	0.92	0.26
	0.5	1.65	1.68	1.55
	0.7	2.86	2.96	4.69
	0.9	7.33	8.21	12.05
	0.95	12.52	15.77	25.98
5	0.1	0.50	0.50	0.00
	0.3	1.50	1.51	0.18
	0.5	2.58	2.60	0.53
	0.7	4.07	4.16	2.26
	0.9	9.12	9.65	5.83
	0.95	13.27	17.26	30.07

Note. Error = (|Simulation – Approximation | / Simulation) * 100 (%)

The approximation gives high precision for M/M/c case as shown in the Table 3.2 and Table 3.3. The system size comparison for M/M/c system was conducted with the known exact solutions not performing simulation. When the service time distribution was Erlang-3 (Table 3.3), it showed good precision with relative errors less than 5%. The precision, however, worsened as ρ increases (especially ρ=0.95), that is, high traffic intensity cases.

Table 3.4 Average Number of Customers for $M/E_3/c$ Systems From Literature

c	*ρ*	Relative Error	
		Kimura (1996)	Miyazawa (1986)
3	0.3 (light)	0.41	9.13
	0.6 (medium)	0.86	3.97
	0.9 (heavy)	0.54	0.64

Table 3.4 illustrates each relative error of approximation from other studies (Kimura, 1996; Miyazawa, 1986). The proposed approximation in this study gives better precision in the light and medium traffic cases, but yields worse result under the heavy traffic condition.

Table 3.5 Average Number of Customers for $M/E_8/c$

c	*ρ*	Simulation	Approx.	Error (%)
3	0.1	0.30	0.30	0.00
	0.3	0.92	0.92	0.15
	0.5	1.64	1.66	1.28
	0.7	2.73	2.87	5.09
	0.9	6.73	7.64	13.46
	0.95	13.45	14.43	7.25
5	0.1	0.50	0.50	0.00
	0.3	1.51	1.51	0.03
	0.5	2.58	2.59	0.45
	0.7	4.02	4.09	1.74
	0.9	8.29	9.11	9.84
	0.95	13.42	15.96	18.92

Note. Error = (|Simulation – Approximation | / Simulation) * 100 (%)

Table 3.6 Average Number of Customers for M/D/c

c	ρ	Simulation	Approx.	Error (%)
3	0.1	0.30	0.30	0.00
	0.3	0.92	0.92	0.25
	0.5	1.62	1.65	1.72
	0.7	2.66	2.82	5.89
	0.9	6.20	7.30	17.63
	0.95	11.20	13.62	21.67
5	0.1	0.50	0.50	0.00
	0.3	1.51	1.51	0.02
	0.5	2.57	2.58	0.42
	0.7	3.94	4.05	2.72
	0.9	7.79	8.79	12.86
	0.95	12.84	15.17	18.16

Note. Error = (|Simulation – Approximation | / Simulation) * 100 (%)

Similar to the results in Table 3.2 and Table 3.3, percent relative errors of $M/E_8/c$ and M/D/c systems increase as traffic intensity increases (Table 3.5 and Table 3.6). For light and medium traffic cases, the approximation yields fine precision, but not in heavy traffic.

Based on the numerical analysis conducted previously, the approximation in this study shows fine precision for small number of customers and light/medium traffic. Therefore, the approximation algorithm provides various types of performance measures (average values of system size, time in system, waiting time, etc.) easily with high precision.

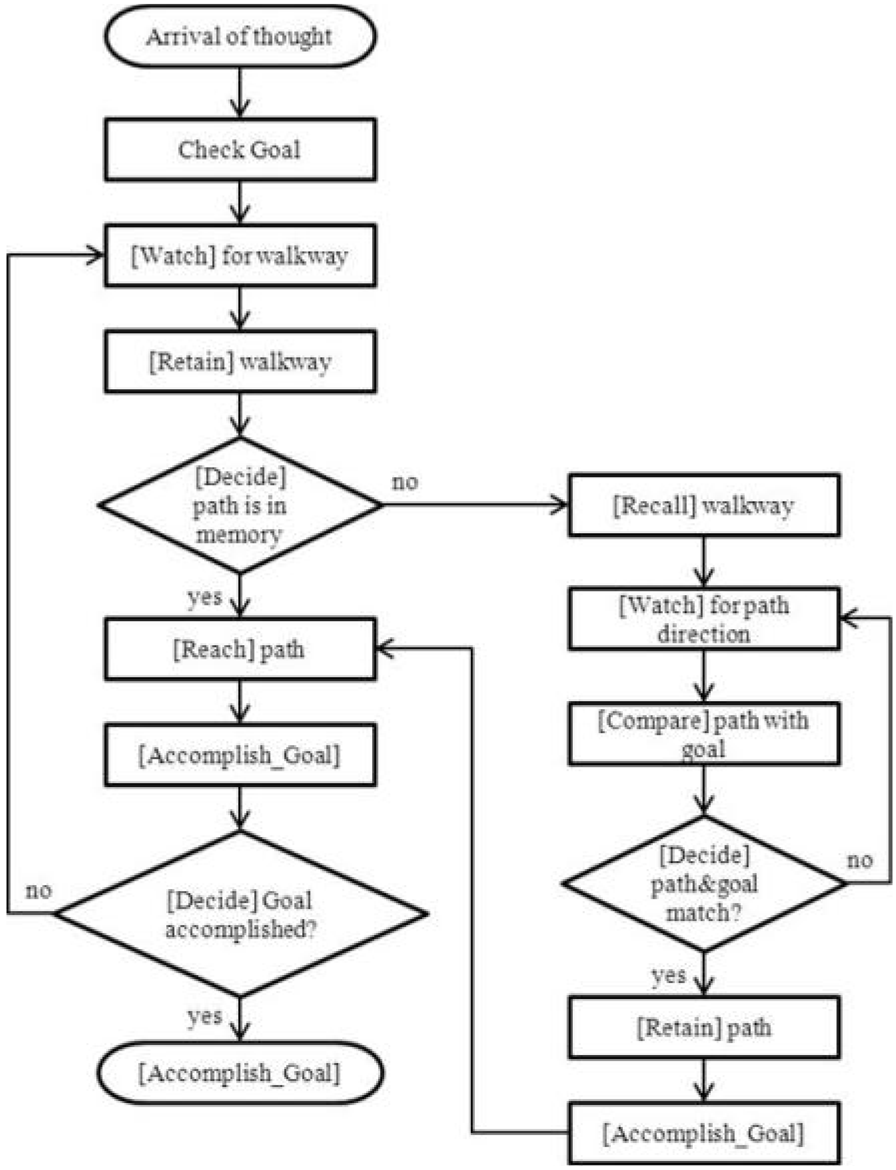

Figure 3.4 Procedural Task Flow of the Visual Search in Pedestrian Navigation

Figure 3.4 illustrates the procedural task flow that described in the previous chapter as well, and it was utilized to implement the visual search task in pedestrian navigation and to predict task completion time, which is time between stimulus presentation and action initiation using processing logic, decision rule and GOMS style task operators. Based on the task description in Table 3.1 and the procedural task flow in Figure 3.4, the model was implemented using Java programming language (JDK version

6). Since this study does not present a real-time walking simulator that participants involve navigational experiments, the simulation run was started from the moment of stimulus presentation. Each simulation run of cognitive model in the study was treated as an actual experiment: the queueing network cognitive model was presented with ten stimuli occurring at random interarrival times ranging from five to sixty seconds and the simulation was replicated 1100 times treating first 100 times as a warm-up period.

Table 3.7 displays estimated information processing times using the existing queuing network model proposed by Feyen and Liu (2001) and the one from this study. Empirical study results also reported in Table 3.7 to compare it with predicted values from both models.

Table 3.7 Information Processing Times (in seconds) Comparisons for the Reaction Time Task

Processing Stage	Methods	Minimum	Mean	Maximum
Perceptual	Feyen & Liu	0.050	0.098	0.196
	Model	0.125	0.127	0.128
Cognitive	Feyen & Liu	0.026	0.068	0.155
	Model	0.054	0.055	0.056
Motor	Feyen & Liu	0.030	0.069	0.148
	Model	0.073	0.074	0.075
Total	Feyen & Liu	0.106	0.235	0.499
	Model	0.253	0.256	0.259
	Empirical (trunc.) 95 % CI: (0.251,0.261)	0.217	0.256	0.333
	Empirical (all) 95 % CI: (0.475,0.542)	0.217	0.509	1.683

Note. Empirical (trunc.) contains all reaction time data up to 33rd percentile from the fast (immediate) response group.

As mentioned in the previous chapter, participants were free to choose their own moment of action initiation, so the observed response time had a huge gap between minimum and maximum of response times. The response time was grouped into three equally spaced percentiles, and the minimum, average, maximum and 95 % confidence interval of the first 33rd percentile of task completion times were reported in the Table 3.7 labeled with 'Empirical (trunk.)' since it was believed that these response times were observed from those who took actions immediately after stimulus presentation, which is more appropriate to the current state of model development. As shown in Table 3.7, the predicted minimum, mean and maximum reaction times fell within a 95% confidence interval of truncated reaction time. However, Feyen's had a wider gap between minimum and maximum of reaction times than the proposed model's outcome as well as empirical study results.

3.6 Conclusion and Future Work

The study effort was to construct a framework of cognitive information processing structure for cognitive tasks in order to obtain predicted value of cognitive processing time using stochastic characteristics of queueing systems. While existing queueing models assumed that stimulus interarrival and processing (i.e., service time) times are exponentially distributed, this study endeavored to develop a model that is context-free of service time distribution as long as its first and second moment are known.

Since there is no exact solution for M/G/c queues, a transform-free approximation method for obtaining basic solution for M/G/c queueing system was developed. The system size distribution for the number of customers (less than or equal to c) was obtained by initiating from the M/M/c model, using the ratio of M/G/c and M/M/c, and traffic intensity. When the number of customers is greater than c, a queueing area was regarded as a set of each separate waiting space rather than the entire queue as a whole.

Types of offered load at an arrival epoch on each waiting space were classified to analyze the system thoroughly.

The model gives high approximation precision when the traffic intensities were light, medium and medium-high. Since this approximation is transform-free, there is no need to take the reverse transformation and the computation procedure is simple. Especially, system size distribution encompasses the simple format of only first and second moment of service time that requires less memory space and computation time. This study may contribute to performance analyses of multiple access telecommunications system and inventory system, as well as construct cognitive architecture in order to compute the information processing time.

After taking generalized expansion of the system to a network structure, server processing and GOMS style task operator logics were added to the network model to construct a cognitive information processing system. Compared to the empirical study outcomes discussed in the previous chapter, the minimum and maximum reaction times were appropriately predicted that fell within a 95% confidence interval of actual mean reaction time. The current realization of cognitive information processing model is pertinent to investigate the cognitive structure of the simple reaction time task as well as predict its mean completion time. Appropriate tasks, for example, would be key-stroke level of simple tasks, visual search for detecting obstacles, color detection, and so forth.

Theoretically running the model until it converges is appropriate based on the natural characteristics of queueing system, but the task considered in the study was simple enough to reach a convergence and the simulation run was terminated with 3% of target error rate. Modeling running under the various scenario settings would be necessary to validate the performance and sensitivity of the model comparing more empirical outcomes so that the model can be applied to various situations. Also, an additional model development for estimating mental workload is planned based on one of the model outcome, i.e., utilization, which appropriately fit mental workload measurement using NASA-TLX.

So far cognitive networks that represent visual system have been implemented. Additional sensory systems, such as auditory and somatosensory systems, will be considered in order to improve model versatility that can appropriately represent complex multiple tasks as if human operators perform primary and secondary tasks simultaneously. Empirical studies will also be conducted to validate cognitive model performance and its reliability while varying values of system and environment parameters.

This model is under the consideration of implementing as a cognitive module for the pedestrian simulator based on cellular automata and state-dependent multiserver queueing network systems. It is expected that it better represent pedestrian behavior with respect to cognitive information processing and decision making.

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CHAPTER IV

ANALYZING PHYSICAL AND PSYCHOLOGICAL PEDESTRIAN BEHAVIOR THROUGH NATURALISTIC AND EXPERIMENTAL OBSERVATIONS

4.1 Abstract

This study presents methods to quantify pedestrian traffic behavior, and analyze physical and cognitive behavior from the real-world observation and field experiment. Video footage from indoor and outdoor corridor settings is used to quantify pedestrian behavior. Existing surveillance footage from a university building was used to investigate naturalistic pedestrian behavior. A field experiment was also conducted under 20 scenarios of varying pedestrian density, flow combination, and speed. A coordinate conversion technique that maps images in the footage onto a real floor plan coordinate system was applied for image processing and data collection. This study has empirically examined pedestrians' preferred minimum distance from obstructions in order to identify association with their travel performance. Walkability survey questionnaire was developed to assess perceived pedestrian comfort, performance and satisfaction in waking. Data on image coordinate were converted onto a real floor coordinate with high precision and low standard errors. Pedestrian space, the number of flow directions and speed class influenced observed speed and pedestrian zoning. Walkability was invariant as long as personal distance is secured. Pedestrians tend to keep more distance from other pedestrian than obstacles on walkway while changing their speed and direction.

Future work related to planned empirical studies, modeling strategies and walkability survey reliability are presented.

Keywords: pedestrian behavior, image analysis, coordinate conversion, traffic performance, pedestrian zoning, walkability

4.2 Introduction

Pedestrian behaviors and traffic flows have only been given limited attention in recent research. One of the reasons is that tools to analyze pedestrian behavior and pedestrian traffic flows are scarce. There is a current need to more accurately depict pedestrian movements and behavior. Understanding pedestrian behavior could lead to improved guidelines for transportation facility design. This research presents a means of obtaining such data, and seeks to incorporate empirical studies and data into the authors' ongoing pedestrian simulation model development (Usher & Strawderman, 2008).

Behavioral studies found in the literature define a number of strategies used by pedestrians as they navigate through a crowd. Related to collision avoidance, pedestrians tend to either change their trajectory or change their speed. They also have a number of strategies that are employed when passing other pedestrians. These collision avoidance patterns are impacted by the individual behavior, as well as the density of the crowd (Bierlaire, Antonini, & Weber, 2003). Pedestrians demonstrate a territorial effect in that they tend to keep a minimum distance from others in the crowd. They also exhibit a preferred minimum distance when passing obstacles. This preferred distance, or territory, is smaller as the pedestrian hurries and is also reduced with growing crowd density (Helbing & Molnár, 1997).

A pedestrian's speed and trajectory could be impacted by their goals, urgency, and the surrounding crowd. The change in speed is likely compounded by the fact that pedestrians will be faced with many more decision points when navigating through a dense crowd. They will have to have concrete situation awareness (SA), taking in a high amount of information, to navigate the crowd with appropriate actions. Pedestrians have a tendency to choose paths to their destination that minimize the need for angular displacements, that is, gradual and smooth changes in trajectory (Turner & Penn, 2002).

Another important facet of pedestrian behavior is zoning. Individual pedestrians tend to keep a minimum distance from others in the crowd. Willis et al. (2002) have found that the actual distance between people or objects depends both on the type of pedestrian and the type of obstruction. Pedestrians take into account their familiarity with the surrounding pedestrians, uncertainty of the other pedestrians' actions, and prioritization of trajectories when maintaining distance from other pedestrians.

While there have been active researches on SA application in aviation (Endsley, 1995; Bell & Lyon, 2000) and driving performance (Ma & Kaber, 2007), pedestrian SA has been given limited attention in recent research.

Data and statistics from an empirical pedestrian study are useful when they can be applied to model behavior for a general population. With an appropriate pedestrian model, we can predict and analyze the behaviors of pedestrian. However, it is hard to obtain numerical solutions from the model when it is complicated itself or needs to process huge data sets at a time. To resolve this issue, researchers have developed simulation models in pedestrian navigation (Helbing & Molnár, 1997; Daamen & Hoogendoorn, 2003; Antonini & Bierlaire, 2006). There are some common approaches to pedestrian simulation including cellular automata, social force, magnetic force, and queueing network model. Cellular automata consist of an array of grid cells that represent the pedestrian environment (C). Pedestrian agents, that each occupies a single cell at any given time, accomplish movement using updated localized neighborhood rules. In a social force model, pedestrians are motivated to move in response to attractive and repulsive forces exerted by their surroundings (Helbing & Molnár, 1997). Similarly, a magnetic force model is composed of positive poles and negative poles that represent obstructions and goals, respectively (Matsushita & Okazaki, 1993). In queueing network models, nodes represent the current locations that are linked to define possible routes to navigate (Løvås, 1994; Cruz & Smith, 2005).

4.3 Objectives

The study effort was focused on identifying and quantifying the fundamental pedestrian travel behaviors using video footage from real-world observations and controlled field experiments. Whereas modeling and analyzing pedestrian behavior in the literature has mainly focused on physical components of pedestrian characteristics (Helbing & Molnár, 2001; Daamen & Hoogendoorn, 2003; Antonini & Bierlaire, 2006), this study took into consideration of cognitive aspects as well, such as zone of comfort, situation awareness, and subjective walkability. Wakability is defined as the extent to which the built environment is walking friendly (Abley, 2005; PBIC), such that "…the extent to which walking is readily available as a safe, connected, accessible and pleasant mode of transport" (VTPI, 2010). Methods for measuring these cognitive components were also developed and discussed. The findings were combined to develop a pedestrian traffic performance model in association with cognitive components.

4.4 Hypotheses

The problem of interest was to identify the effect of physical and cognitive pedestrian characteristics as well as environment on travel performance and perceived walkability. The measured mean travel performance and mean walkability score were compared under each treatment combination of density and speed. Specific hypotheses included:

H1. Environmental settings will affect the pedestrian travel performance and walkability. Environmental settings include pedestrian density level (LOS grades B, C, D, and E) and the number of flow directions (i.e., unidirectional and bidirectional flows).

H2. Physical walking components will affect the pedestrian travel performance and walkability. Physical components contain speed level (slow, normal, and fast), the number and magnitude of trajectory changes, group size, gender, and personal items.

H3. Cognitive walking components will affect the travel performance and walkability. Trip purpose and pedestrian SA are included in this category. It is hypothesized that there is a difference in distance from corridor wall and other pedestrians with respect to mean travel performance. Walking center and sides of the corridor will differ in mean walking speed.

H4. Pedestrian travel performance measures will be correlated with walkability.

4.5 Study Development Methodology

Data collection methodologies on pedestrian travel performance, spacing propensity and situation awareness assessment were discussed in this section. Video footage and questionnaires were utilized to obtain pedestrian travel performance as well as subjective assessments of navigation.

4.5.1 Experimental Design

In regard to the naturalistic observation study, a completely randomized design on trip purpose (pass, enter, or leave), group size (one or two), and personal items (yes or no) was created to test travel performance.

For the field experiment, an a*b factorial arrangement of treatments on space and speed/flow combinations were created in a random order to assess pedestrian travel performance and subjective walkability. Flow combination and density level had 2*4 treatment combinations fixing speed level to normal as shown in Table 4.1. Speed and density involved 4*4 treatment combinations. Both univariate and multivariate data analyses were conducted to test factorial effects. There were 20 scenarios as shown in.Table 4.1 Exposure to trials was determined using a randomized complete block scheme.

Table 4.1 Experimental Scenario Layout

		Flow comb. (FC)		Space (LOS grade) B	C	D	E
Speed combination.	Normal (100%)	FC	100 50-50	Scenario 1 Scenario 17	Scenario 2 Scenario 18	Scenario 3 Scenario 19	Scenario 4 Scenario 20
	Slow:Normal (40%:60%)	FC	100	Scenario 5	Scenario 6	Scenario 7	Scenario 8
	Fast:Normal (40%:60%)	FC	100	Scenario 9	Scenario 10	Scenario 11	Scenario 12
	S:N:F (33.3% each)	FC	100	Scenario 13	Scenario 14	Scenario 15	Scenario 16

Note: S, N, and F indicate Slow, Normal, and Fast walking speeds. LOS grade in pedestrian space was based on Highway Capacity Manual (TRB, 2000).

4.5.2 Participants

Regarding naturalistic observation, pedestrians were observed using 20 minutes of video footage recorded through surveillance camera system according to the recommendation of pedestrian data collection in the Highway Capacity Manual (TRB, 2000). A total of 68 participants, 55 males and 13 females, were observed.

The number of participants for the field experiment (n) was determined using Cohen's d and power analysis with a type I error (α) of 5% and a type II error (β) of 20%, whereas the power of the test was 0.8 (Ott & Longnecker, 2001) using equation (4.1). The obtained value of n was 87, and this study recruited 100 participants for the experiment. Participants ranged in age from 18 to 37 (mean of 21.4 and standard deviation of 3.9). The numbers of female and male participants were 34 and 66 respectively.

$$n = \frac{(z_{\alpha/2} + z_{\beta})^2}{d^2}; \text{ where } d = \frac{\overline{x}_1 - \overline{x}_2}{s_p} \text{ and } s_p = \sqrt{\frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2}} \tag{4.1}$$

The basic statistics for the sample size determination were from Daamen and Hoogendoorn (2006) (n_1=n_2=75, $\overline{x}_1$=1.46, $\overline{x}_2$=1.33, s_1^2=0.15, s_2^2=0.16. The index 1 describes unidirectional flow and 2 from bidirectional. The calculated values of d and n were 0.3 and 87 respectively.

4.5.3 Task Description

No specific procedure was necessary for naturalistic observation, since footage from surveillance system was used. However, specific tasks were assigned to participants under the various types of scenario settings for field experimental observation. Participants were asked to read the task description in the task information card, and to walk in the constructed corridor as described in task information card (Figure

4.1). Each participant received a task information card that indicates his/her ID, starting/ending locations, and speed class.

Task Information Card

Scenario #:	**01**
Pedestrian ID #:	001
Starting location[1]:	– 1st trial only; – After 1st trial
Ending location[2]:	
Stopping:	You are asked to stop abruptly while walking (anywhere you want), remain stationary for a moment (4-5 sec.), and resume the walking task.
Speed class[3]:	Normal

Slow:	Walk in a leisurely fashion with no rush as if you have plenty of time to get to the class rooms
Normal:	Walk at your own free speed without rush or slowdown
Fast:	Walk as if you are late to class and need to get to class in a hurry

[1] Starting location will be either or , however, participants who are selected to be located on the floor before the scenario start will be given their location numbers (see Figure 2).

[2] Ending location will be given to the participants either or .

[3] There are three types of speed class: slow, normal; and fast. Fast group will be asked to walk as if they are late to class and need to get to class in a hurry. Normal speed group will walk at their own free speed without rush or slowdown. Slow group will be asked to walk in a leisurely fashion with no rush as if they have plenty of time to get to the class rooms.

Figure 4.1 Task Information Card

In order to attain approximate level measures of density, a pedestrian entered the system upon another pedestrian's departure. In each scenario, participants answered three walkability survey questions upon completing the scenario. The experiment included unidirectional and bidirectional flows. Participants were informed of their initial and termination locations, and were classified by normal (control group), fast, and slow speed groups.

4.5.4 Data Collection Methods

The facility for naturalistic observation was an academic building on the university campus. Previously recorded video footage from a first floor corridor was analyzed. The footage was gathered using a motion sensing security camera. In order for it to capture footage, a pedestrian needed to be in the corridor. Figure 4.2 displays the selected site and it was 3 m (10ft) * 22 m (71 ft) with an area of 66 m^2 (710 ft^2). Speed and attribute data were collected on a sample of 68 pedestrians (12 female and 56 male). The footage displayed 20 minutes of behavior during the break between two class periods.

Figure 4.2 Region of Interest and Point of Analysis Designation

Pictures from the experimental trials in the constructed site are shown in Figure 4.3and it displays the experimental setup used for the study. A wall was constructed to simulate an enclosed walkway. Gridlines were placed on the floor for analysis. Each pedestrian wore an identifying number on their shirt, as well as a matching number on a hat. Figure 4.4displays the camera monitoring station used during data collection.

Figure 4.3 Experimental Setup for Empirical Study

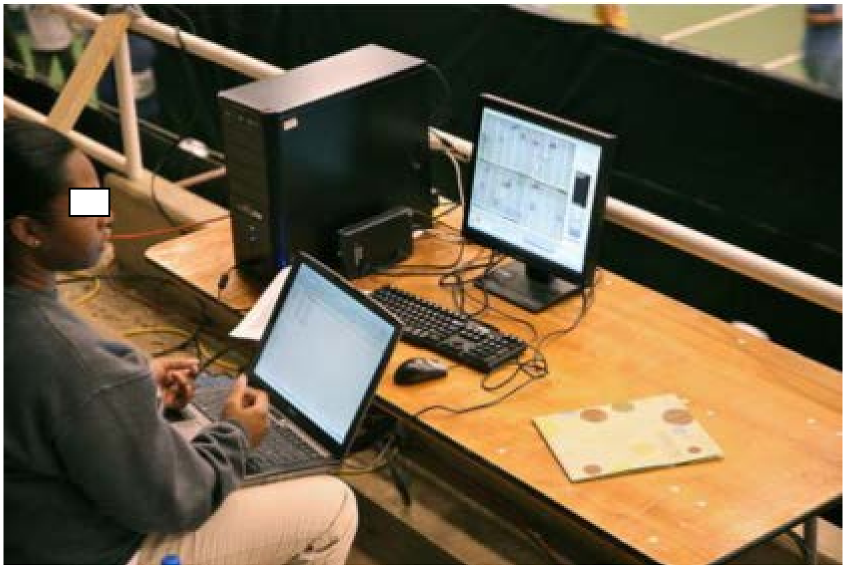

Figure 4.4 Data Collection Apparatus for Empirical Study

A video camera system was used to record participants' walking behavior. The system consisted of a 4-camera security system (including monitoring station) and one high definition digital video camera. Since the viewing distance (scope) of the video camera wais limited (if the height of the mounted camera is not high enough), multiple cameras were necessary to improve the precision of coordinate conversion using overlapped recorded area as shown in Figure 4.5. Four cameras for the detailed view were mounted on top of the guard rail at the end of audience stand (not so high because data coding could be harder as recorded objects get smaller) which was second floor high. One additional overview camera was mounted higher place in the audience stand to ensure wider overview capture.

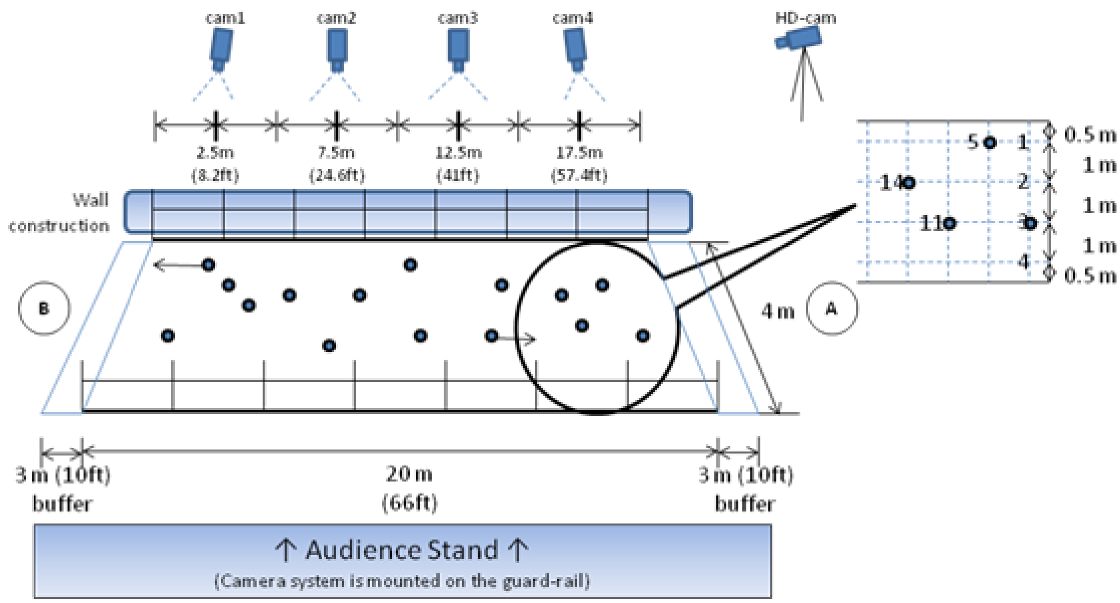

Figure 4.5 Region of Interest and Camera Setting

Fundamental microscopic pedestrian traffic data on speed, density, flow rate, and delay can be obtained by analyzing video footage. The basic information on location and some attributes (e.g., sequential coordinates, gender, group size, etc.) were collected after analyzing footage. The location data were subsequently used to calculate speed, trajectory, and distance from obstructions.

Footage was exported onto a hard drive as an .avi file and converted to a stacked sequence of images at the predetermined frames per second (e.g., 2-30 frames/sec) using VirtualDub, an open-source image processing utility (version 1.8.8), (Lee, 1991-2009). Manual pedestrian tracking was performed for each video frame. To reduce experimenter error and complexity, each frame was trimmed to accentuate the region of interest (ROI) as depicted in Figure 4.2. It displays both the region of interest (solid lines) and the point of analysis (dotted line). Pedestrians who passed through the ROI were included in the study.

The image coordinates that represent pedestrians' current positions in each frame were acquired using ImageJ (Rasband, 1997-2008), an image processing and analysis tool (version 1.42), assuming that the middle point of a pedestrian's feet represents his/her current location (x_{image}, y_{image}) in each frame as showed in Figure 4.2. The second assumption was that the coordinate for the overlapped pedestrian by the front or taller people was forecasted with his/her previous trajectory coordinates taking moving averages. Each pedestrian was assigned a unique indentifying number. The pedestrian's image coordinates were recorded in a matrix format while tracking pedestrian coordinates frame by frame. This sequence of work continued from the time the pedestrian entered the footage until they exited. Table 4.2 shows a sample of the data collected, including pedestrian ID, frame numbers, and image coordinates.

Table 4.2 Coded Data on Image and Estimated Coordinate Values by Frame

Ped ID	Frame#	X(image)	Y(image)	X(real)	Y(real)	Camera
75	661	515	182	4.650164	2.452685	cam1
75	662	496	184	4.475268	2.474824	cam1
75	663	486	184	4.383268	2.473634	cam1
75	664	473	184	4.263668	2.472087	cam1
75	665	458	182	4.125764	2.445902	cam1
75	666	444	181	3.997012	2.432036	cam1
75	667	430	182	3.868164	2.44257	cam1
75	668	422	182	3.794564	2.441618	cam1
⋮	⋮	⋮	⋮	⋮	⋮	⋮

Due to the camera angle and lens distraction, coordinate conversion is required to analyze pedestrian traffic performance and related behaviors because the acquired image does not represent the rectangular corridor area in reality. Therefore, the real floor plan coordinates (x_{real}, y_{real}) were estimated from the image coordinates (x_{image}, y_{image}) with the trimmed data set from ROI. The calibration process started with recording current image coordinate matrix, followed by taking the affine transformation for both length (x_{real}) and width (y_{real}) with (x_{image}, y_{image}) and β's (Tsai, 1987; Teknomo, 2006). Next, multiple linear regression, using stepwise method, was taken to compute the estimated values of parameters ($\widehat{\boldsymbol{\beta}}$'s):

$$\begin{cases} \hat{\mathbf{x}}_{real} = \hat{\boldsymbol{\beta}}_{0x} + \hat{\boldsymbol{\beta}}_{1x}\mathbf{x}_{image} + \hat{\boldsymbol{\beta}}_{2x}\mathbf{y}_{image} \\ \hat{\mathbf{y}}_{real} = \hat{\boldsymbol{\beta}}_{0y} + \hat{\boldsymbol{\beta}}_{1y}\mathbf{x}_{image} + \hat{\boldsymbol{\beta}}_{2y}\mathbf{y}_{image} \end{cases} \tag{4.2}$$

Equation (4.2) was applied to estimate parameters and predict real coordinates with randomly sampled coordinate data, which were directly measured from the corridor floor.

4.5.5 Independent Variables

4.5.5.1 Independent Variables for Naturalistic Observation

The identified factors involved in naturalistic observation were trip purpose, size of the walking group, and personal items (food, backpack, etc) and they were treated as independent variable. Based on observation, there were three types of trip purposes: passing between class rooms; entering the building; and leaving from the building. People in this building corridor walked alone or in groups talking to another pedestrian. While there are uncontrollable and limited numbers of independent variables in naturalistic observation, other types of factors were discussed below for conducting field experiments.

4.5.5.2 Independent Variables for Field Experiment

4.5.5.2.1 Speed Level

As described in task information card, there are three levels for speed, and each speed level was assigned appropriately to each scenario setting. Since people do not walk at exact speed, participants were asked to walk at their own speeds, which were classified by slow, normal, and fast.

4.5.5.2.2 Number of Pedestrians

Pedestrian density level, that is the number of pedestrians in the system, were randomly populated (i.e., initial coordinate locations for each participants were predetermined before each scenarios begins.) in the system before new pedestrians arrive based on the pedestrian density grade in Highway Capacity Manual (TRB, 2000). As soon as a pedestrian leaves from the system, a new pedestrian enters the system to maintain the current setting of density. Pedestrians who completed the navigational tasks were asked to return to the waiting area to prepare for the next trial.

4.5.5.2.3 Flow Combination

It was constructed to conduct the experiments under the unidirectional and bidirectional flow situations with regard to equal flow distributions for both directions.

4.5.6 Dependent Variables

4.5.6.1 Traffic Performance

Walking speed is calculated in order to analyze microscopic pedestrian behavior. For any observation time n, the distance between frame n and n+1, for any pedestrian navigation, is calculated in Euclidian space.

$$\text{Distance } (m) = \sqrt{(x_{n+1} - x_n)^2 + (y_{n+1} - y_n)^2} \tag{4.3}$$

This sequence of work continues from the birth (arrival epoch) of a pedestrian to their death (departure) within the specified ROI tracing pedestrian trajectory frame by frame. Once we finish tracking the first pedestrian's trajectory in ROI, we move our focus onto the second pedestrian, and continue tracking until there is no pedestrian left in the last frame. Instantaneous pedestrian speed was obtained using the distance calculated in equation (4.3) and the frame rate. We assumed that the initial speed of each pedestrian is zero, and we did not take it into account when calculating average instantaneous speed (see equation (4.4).).

$$\text{Instantaneous speed } (m/s) = (\text{distance}) \times (\text{frame rate}) \tag{4.4}$$

The next fundamental characteristics of pedestrian traffic flow are flow rate and density. These were chosen as they have high impacts on the service level of pedestrian facilities (e.g., level A through F with ranges, level A is the best) as well as the design guidelines and policies for pedestrian facilities. Flow rate is defined as the number of pedestrians passing a point of analysis (as depicted in Figure 4.2) in a unit of time, that is, pedestrians per width of walkway per time unit (Friun, 1971; TRB, 2000)

$$\text{Flow rate(ped/min/m)} = \frac{\#\text{pedestrians}}{(\text{observation time}) \times (\text{walkway width})} \tag{4.5}$$

Pedestrian density is the number of pedestrians within the given unit of area (ped/m^2). Area module (i.e., pedestrian space), the reciprocal of pedestrian density (m^2/ped), is used in this study because it is easier to manage and relates to facility design. As stated previously, instantaneous average speed was recorded tracking all the pedestrians in each frame, and instantaneous pedestrian space was calculated for each frame by dividing the area of ROI by the number of pedestrians in each frame. Flow rate was also calculated and it is equivalent to the product of instantaneous average speed and density in each frame.

4.5.6.2 Walkability

As a pedestrian perceived LOS, walkability assessment was conducted by participants since LOS methodology in the Highway Capacity Manual (TBR, 2000) has studied and calculated at researchers' point view without considering how pedestrians themselves feel. Walkability assessment allows pedestrian participants to express how they felt and what they experienced during the trials as shown in Figure 4.6. This was used as a subjective measure of LOS to investigate the impacts of density level and flow combination on walkability measure (how pedestrians felt) and the relationship between subjective and objective (TRB, 2000) LOS measures.

Walkability Survey

Scenario Number: 01

Instruction: At the end of the Scenario, please complete the three questions below by placing 'X' in the box that most closely matched your feelings. Please consider ONLY the scenario that was just completed.

Comfort

I had adequate space to walk during the trials.

Strongly Disagree	Disagree	Slightly Disagree	Neutral	Slightly Agree	Agree	Strongly Agree
1	2	3	4	5	6	7
☐	☐	☐	☐	☐	☐	☐

Performance

I was able to maintain my desired walking speed during the trials.

Strongly Disagree	Disagree	Slightly Disagree	Neutral	Slightly Agree	Agree	Strongly Agree
1	2	3	4	5	6	7
☐	☐	☐	☐	☐	☐	☐

Satisfaction

It was easy for me to walk during the trials.

Strongly Disagree	Disagree	Slightly Disagree	Neutral	Slightly Agree	Agree	Strongly Agree
1	2	3	4	5	6	7
☐	☐	☐	☐	☐	☐	☐

Figure 4.6 Walkability Assessment Questionnaire

4.5.7 Additional Considerations

4.5.7.1 Ratio of Side Walking

The phenomenon of side walking is frequently observed in congested and multiple flow situations. It is defined as the walking behavior that can be observed from participants who turn their steps either right or left side to avoid collision and keep current speed (Fukamachi & Nakatani, 2007; Blue *et al.*, 1997). The proportion of side steps was obtained by counting the number of frames that contains sidle steps and divides it by total number of frames that includes trajectory changes. The rate of side walking was obtained under the pedestrian density levels of C, D, and E, since pedestrians' room for free walking is limited from level C.

4.5.7.2 Zone of Comfort

Fruin (1971) discussed the space that pedestrians tend to keep some distance between themselves and obstacles the so-called pedestrian buffer zone. He categorized the level of pedestrian areas into four types: touch zone (radius of individual buffer is 0.3 m); no-touch zone (0.46 m); comfort zone (0.53 m); and circulation zone (0.61 m). In this study, the pedestrian zone (private sphere) was categorized into two groups, which are of less and greater than or equal to zone of comfort to examine the impact of zone of comfort on observed pedestrian speed.

When pedestrians are confronted with an imminent collision, they make a decision to pass another pedestrian changing their speed or trajectory so as to maintain individual preference of mutual distance. In this case, pedestrians change their speed or trajectory by sidesteps and adjustments (Fukamachi & Nagatani, 2007; Blue *et al.*, 1997) to keep their current direction as they move toward their goal destination maintaining their preferred minimum distance from other pedestrians and obstacles. It was presumed that a trajectory change of 45 degree or less between two consecutive frames was a side step, which means no trajectory change was made, when measuring changes in trajectory.

Using equation (4.3), the minimum distance from other pedestrians and obstructions (e.g., other pedestrians, corridor furniture, wall, etc.) was measured in each and every frame to obtain individual pedestrian's preferred zone of comfort as they navigate. All pedestrians' minimum distances were recorded in line with instantaneous speeds (see equation (4.4).) in each frame to examine the association between them. The initial hypothesis was that the smaller zones of comfort pedestrians have the slower speed they take. The reason this was expected is because they cannot navigate at full speed under the congested or restricted area.

4.5.7.3 Pedestrian Situation Awareness

To subjectively rate each pedestrian's situation awareness (SA), the individual pedestrian trajectory and level of perception (e.g. what they are looking towards) were recorded. Observers then classify the level of situation awareness from their observations based on the way of classification described in this section. A similar technique, Subjective Observer's Rating SA (SARS), has been proposed by Bell and Lyon (2000), in which 31 behavioral elements of SA were identified, including pilots' perception, tactical planning ability, communication, information interpretation, and appropriate action. Although they presented a variety of elements of SA, it may not be appropriate to assess pedestrian SA because it is a completely different field of study from pilot SA application.

To construct an observer rating checklist, five key elements of SA within two categories were selected based on pedestrian literature (Antonini *et al*., 2006; Hoogendoorn & Bovy, 2005; Jian *et al*, 2005; Helbing et al., 2001; Blue *et al*., 1997). The two categories, self-organization and collision avoidance, are generally accepted elements that affect individual's navigational performance (e.g., collisions, way-finding, travel time, etc.). Both are essential elements, which pedestrians need to possess while they navigate in crowd (e.g., collision immanent or emergent situation) efficiently.

The first category, self-organization, means that behavioral patterns are not externally planned, prescribed, or organized, for example, by traffic signs, laws, or behavioral conventions. This phenomenon is indispensable for the optimization of pedestrian flows, as they determine their efficiency (measured as a pedestrian's average speeds are compared to desired speed) and potential sources of obstructions. These interactions are more reactive and subconscious as compared to strategic considerations or communication (Helbing *et al*., 2001). Pedestrians frequently form flow lanes when they walk in the crowds to maximize their navigation performance by maintaining current speed and direction as they move toward their goal destination (Antonini *et al.*, 2006). Another element of self-organization is a leader/neighbor following characteristic. It also ensures the efficiency of movement by using the path that the leaders have already made.

The second category, collision avoidance, entails divergence, gap selection, and passing strategy with changes in speed and/or trajectory based on what pedestrians perceived. Unlike self-organization, this characteristic is relatively proactive and conscious rather than planned or organized behavior. Pedestrians can make a sound decision when they have high quality of environment perception and concrete understanding of situation. Collision avoidance category includes perception, and appropriate changes in speed and trajectory. When a pedestrian realizes that a collision with another pedestrian is imminent, they generally decide a course of action.

Speed and attribute data were arranged with all pedestrians, who walked toward the surveillance camera showing their faces, to observe pedestrians' perception and reaction to the environment change more easily. If a pedestrian was cautious and vigilant enough watching his/her surroundings, then raters assessed higher score in 'perception of surroundings/neighbors' element. In the same fashion, pedestrians who did not take a proper action to avoid collision or an effective path following (e.g., self-organizing) though they noticed current situation, a poor score was given. A subject-matter-expert (SME) and a peer rated pedestrians' SA with the observational checklist that contains key subjective observer's rating SA elements described previously and a 5-point Likert rating scale system (i.e., 1=unacceptable, 2=poor, 3=neutral, 4=acceptable, and 5=outstanding). The SME holds an Institutional Review Board (IRB) certificate after completing the training about human subject research, and has involved in the pedestrian study. The peer is working in the building where the surveillance camera is facilitated, and is familiar with the site. The peer and SME watched different video footage, which were recorded by the same camera, and they were instructed how to grade pedestrian SA. They were not informed about traffic flow in the selected footage such as speed, travel time, density, flow rate, etc.

4.5.8 Procedure

No specific procedure was necessary for real-world observation, since footage from surveillance system was used and footage handling method was described previously. However, a specific procedure was developed for conducting field experiments.

Upon arriving participants were given a verbal description of the study and its objectives, and were asked to read and complete the IRB approved informed consent documents. Each pedestrian were given a set of task information cards, one for each scenario. Each card contains information about that scenario, including their ID numbers, starting and ending locations, and speed classes. Participants were also given verbal and written explanations of how to answer to each question on the walkability assessment sheet, which is on the backside of the task information card.

Participants were asked not to talk to each other during trials as far as possible in order to avoid group behavior. Also, they were asked not to look around out of the corridor setting. At the start of each scenario, a selected number of pedestrians began the trial in the corridor. These pedestrians were instructed about where to stand by the researchers. Once the trial begins, other pedestrians begin entering the system. As soon as one participant left from the system, the next waiting pedestrian entered the system. They looped through the corridor (e.g. reentering the entrance queue after completing the walk) until the trial ended. Both the start and stop of the trial were indicated by an auditory announcement made by a researcher. After participants finished the scenario, they were asked to answer three questions about walkability (i.e., subjective LOS assessment). Three specific tasks were assigned followed by trial runs for the experiment. Two trial runs were given to participants for an opportunity to better understand the tasks for the study. The trial runs were intended to demonstrate the trial procedures before data collection begins.

Unidirectional flow tasks included scenarios one through 16. Pedestrians were asked to follow investigators' requests and to walk under the unidirectional flow formation. The randomly selected and ordered sequence of scenarios was scenarios 13, 9, 10, 2, 15, 6, 4, 1, 3, 14, 16, 5, 11, 7, 8, and 12. After each scenario, each participant answered the three survey questions on the back of their task card.

Bidirectional flow tasks had the same as unidirectional case, but participants had two different stating locations. These settings included scenarios 17 through 20. The order of scenario runs was scenarios 20, 18, 19, and 17. After each scenario, participants answered the three survey questions on the back of their task card.

4.5.9 Data Analysis

Appropriate descriptive statistics were obtained for each dependent variable (e.g., means and standard deviations). Regression models were developed to predict task performance in association with independent variables as well as to fit the walking speed as functions of pedestrian density, number of flows, gender, and body weight.

Multivariate analysis of variance (MANOVA) with performance measures was taken to test hypotheses described previously, regarding factorial effects of density and speed level combinations with respect to mean performance measures. As well, Fisher's protected LSD (least significant difference) and two-sample t-tests were used where appropriate. Correlations between each of the dependent variables were also computed. All findings were considered significant at an alpha (significant level) of 0.05 unless otherwise stated. The SAS 9.2 for windows was used for all statistical analysis.

4.6 Results

4.6.1 Naturalistic Observation

A variety of measures were calculated to describe the ob-served pedestrian behavior. A summary of these measures are shown in Table 4.3.

Table 4.3 Overall Pedestrian Measures

Traffic performance measures	Mean	Standard deviation
Travel distance (m)	9.52	7.44
Average instantaneous speed (m/s)	1.00	0.69
Average instantaneous density (ped/m^2)	0.04	0.02
Instantaneous delay (s)	0.12	0.21
Distance from wall (m)	0.87	0.40
Distance from other pedestrians (m)	1.72	1.52
Magnitude of trajectory change (degrees)	24.15	39.28
Number of trajectory changes	7.98	12.41

4.6.1.1 Speed

The average instantaneous speed of all observed pedestrians was 1.00 m/s, with a standard deviation of 0.69. The average is lower than Fruin's (1971) average speed of 1.35 m/s (standard deviation of 0.25) and the average speed for young pedestrians, 1.46 m/s, reported by Fitzpatrick *et al*. (2006). The difference between the observed pedestrian speed and those reported in literature is most likely due to the fact that the pedestrians in the study tended to spend a lot of time stationary while talking to neighbors. It was observed that women's walking speeds (0.68 m/s) are slower than that of men (1.06 m/s). These values are also lower than the values reported by Fitzpatrick *et al*. (2006).

The impact of these pedestrian characteristics on speed is shown in Table 2. Pedestrians walking alone moved at a faster travel speed than those in groups ($F=8.74$, $p<0.001$). Additionally, pedestrians that were leaving the building or simply passing through had a higher speed (F=7.52, p=0.001). This is likely due to the fact that those 84% of pedestrians classified as entering the corridor experienced delays in travel. Of those leaving the corridor, 40% experienced delays, while only 13% of pedestrians passing through the corridor (traveling room to room) were delayed. Many pedestrians encountered delays in their travel (talking to another pedestrian, waiting on an elevator, etc.). When the delayed data are removed from the sample, the average instantaneous speed increases (reaching 1.34 m/s). This result is much closer to the results reported by Fitzpatrick et al. (2006).

Table 4.4 Speed by Pedestrian Type

	Sample size	Mean (m/s)	Standard deviation
Entire sample	68	1.00	0.69
Group size			
1	57	1.14	0.74
2	26	0.64	0.47
3	9	0.37	0.21
4	4	0.10	0.11
Gender			
Male	55	1.06	0.69
Female	13	0.68	0.49
Delayed			
Yes	64	1.47	0.24
No	4	0.96	0.68
Trip purpose			
Pass	16	1.16	0.68
Enter	25	0.70	0.42
Leave	27	1.17	0.39
Personal items			
Yes	19	1.01	0.46
No	49	0.99	0.55

Based on the appearance of pedestrians in the video footage, it was assumed that the age of all the pedestrians fell in the young category (less than 60 years). Therefore, it was not possible to differentiate the impact of pedestrian age on their behavior using this dataset. The possession of a personal item (e.g., backpack, book, and food/drink) did not appear to have an impact on the pedestrian's travel speed.

4.6.1.2 Trajectory Change

The path of each pedestrian was tracked frame by frame and described by calculating the number and magnitude of trajectory changes. The average trajectory magnitude for all pedestrians in the sample was 24.15 degrees. This was significantly affected by the pedestrians' average instantaneous speed ($F=10.76$, $p=0.002$). Slow walkers, defined as having a speed of less than 0.7m/s had an average trajectory change magnitude of 41.55 degrees, whereas fast walkers had an average magnitude of 29.14 degrees ($F=1.31$, $p=0.256$). Therefore, fast walkers were able to make more minute changes in their path, whereas slow walkers made abrupt and drastic changes.

Another measure of pedestrian trajectory was the number of trajectory changes made. This metric was defined as how many times each pedestrian made a trajectory change greater than 45 degrees (if a pedestrian made a 40 degree of trajectory change within two consecutive frames, it would be minuscule since pedestrian tracking was conducted frame by frame). Anything less than this was considered a side step or simple maneuver. The average number of changes was 8.70. However, this was significantly different based on group size ($F=3.37$, $p=0.024$). Individual pedestrians made an average of 8.37 trajectory changes, whereas pairs made an average of 2.57 changes showing greater forward movement force than the single pedestrians. Additionally, the average instantaneous speed was a significant factor in number of trajectory changes ($F=4.04$, $p=0.003$). Slow walkers made an average of 13.32 changes, whereas fast walkers made only 2.59 changes.

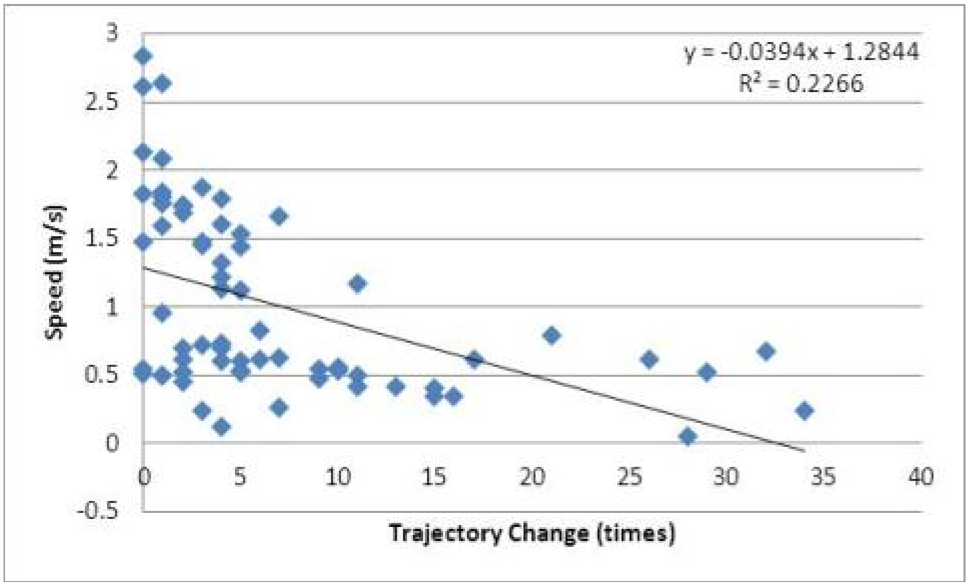

Figure 4.7 Speed as a Function of Trajectory Change

The number of changes in trajectory had a negative linear relationship with pedestrians' average instantaneous speed (r^2=0.22, Speed = 1.2844 – 0.03937*TrajectoryChange) as illustrated in Figure 4.7. As pedestrians made fewer trajectory changes, their speed was faster than those who made more changes. The mean number of trajectory changes per pedestrian was 8.7. There was a significant difference ($p<0.001$) in average instantaneous speed between those that made fewer than 8.7 trajectory changes (1.2 m/s) and those that made more trajectory changes (0.48 m/s).

Pedestrians with lower average instantaneous speed showed numerous meandering or stationary behaviors throughout the observations. To account for this lack of movement, non-homogeneous data was trimmed and an improved linear association was found (r^2=0.6, Speed = 1.867 – 0.1147*TrajectoryChange). There was also a significant difference ($p<0.001$) in average instantaneous speed between pedestrians who had an average trajectory change of less than 45 degrees (1.30 m/s) and greater than 45 degrees (0.66 m/s). Totally, 75% of the trajectory changes were 45 degree or less throughout the video footage. Based on the assumption stated previously, whereas any trajectory change less than 45 degrees is considered a side step, it can be said that the majority of people took side steps while changing their speed to avoid collision and maintain their current direction.

4.6.1.3 Zone of Comfort

Two metrics were collected to assess the pedestrians' zones of comfort, in order to describe how much distance they keep from obstructions, walls, and other people. The first measure was the distance a pedestrian was from the closest wall. The average distance was 0.87 meters, and it was greater than Fruin's circulation zone, 0.61 meters (Fruin, 1971). This measure was significantly affected by gender ($F=4.27$, $p=0.043$). Men walked closer to the walls (0.85 meters) than did women (0.94 meters). Distance kept from the wall was also significantly different based on trip purpose ($F=3.80$, $p=0.027$). Pedestrians passing through (room to room) the system kept a larger distance from the wall (1.05 meters) when compared to those entering and leaving (0.88 meters and 0.86 meters).

The second measure for zone of comfort was distance from other pedestrians, referred to as zoning. The average zoning distance was 1.72 meters. This is twice the size of the average distance kept from the wall, showing that people prefer to walk closer to objects rather than other people. Zoning was marginally affected by gender ($F=3.37$, $P=0.071$). Women kept further distance from others (2.18 meters) when com-pared to men (1.68 meters). Another significant factor associated with zoning was trip purpose ($F=5.27$, $p=0.008$). The largest average zoning distance was found with leaving pedestrians (2.36 meters), followed by passing (1.80 meters) and entering pedestrians (1.06 meters).

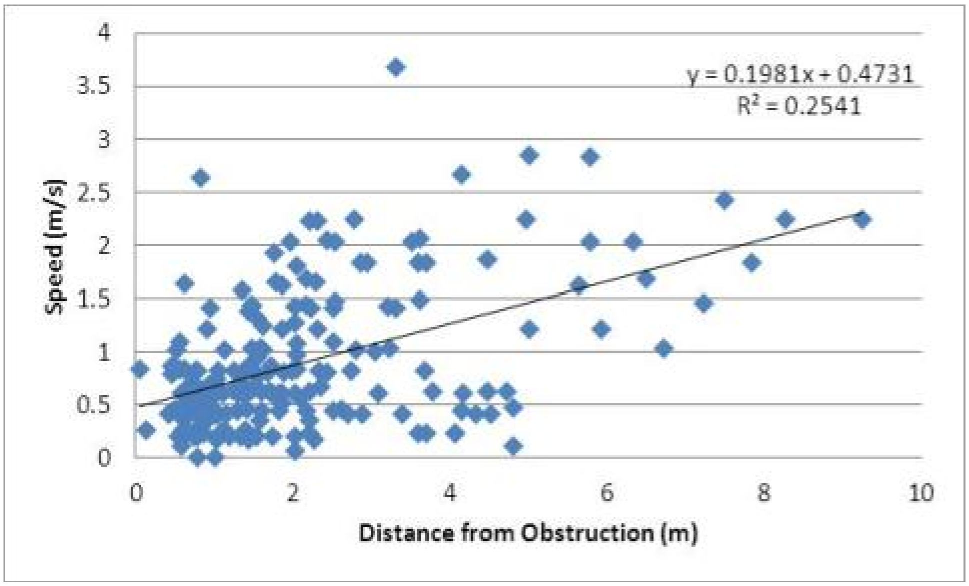

Figure 4.8 Speed as a Function of Distance from Obstruction

Figure 4.8 displays pedestrian speed as a function of distance from obstructions (e.g., other pedestrians, walkway border and obstacles). The function represents a linear association (Speed = 0.4731 + 0.1981*Distance) with an r^2=0.25. Based on this relationship, it is inferred that pedestrians who have a greater minimum distance from obstructions walk faster than those who have smaller minimum distance.

4.6.1.4 Pedestrian SA

Pedestrian SA was rated under the light pedestrian density environment. Even though this is not the situation that may cause catastrophic events, evaluating pedestrian SA, however, could give useful insight to develop pedestrian traffic flow model that simulates evacuation or emergent situation. Table 4.5 shows pedestrian SA score by core behavioral elements in walking.

Table 4.5 Pedestrian SA Scores

ID	Rater	Self-organization		Collision avoidance			Total score
		Leader /neighbor following	Maintain speed / direction	Appropriate trajectory change	Appropriate deceleration	Perception of surroundings / neighbors	
1	SME	3	4	4	4	5	39
	Peer	3	4	4	4	4	
2	SME	3	4	4	2	5	35
	Peer	3	4	3	3	4	
33	SME	3	3	4	4	5	37
	Peer	3	3	4	4	4	
38	SME	4	2	3	2	4	33
	Peer	4	3	4	3	4	
39	SME	4	2	3	2	4	32
	Peer	4	3	3	3	4	
46	SME	4	2	3	2	4	29
	Peer	4	2	2	2	4	
47	SME	4	3	3	2	3	29
	Peer	4	2	3	2	3	
52	SME	3	4	4	4	4	40
	Peer	3	3	5	5	5	
53	SME	4	5	4	4	5	46
	Peer	4	5	5	5	5	
60	SME	4	2	4	4	4	39
	Peer	4	3	4	5	5	
63	SME	3	2	2	2	4	27
	Peer	4	2	2	2	4	
64	SME	4	4	4	3	4	37
	Peer	4	3	4	3	4	

As literature in SA under the dynamic, complex tasks situation (e.g., Ma & Kaber, 2007; Bell & Lyon, 2003; Endsley, 1995, etc) reported the operator task performance has a strong positive association with SA score (either subjective or objective rating), the study presumed that the faster pedestrians tend to have better SA and a high amount of information to help maintain their desired speed, taking appropriate actions in advance. However, pedestrian SA was almost uncorrelated with average speed (r^2=0.0207, F=0.21, p=0.656). This may be due to the fact that a couple of possible influential points were found at the left top of Figure 4.9 because these pedestrians maintained their speed though they were eating and reading while walking. Therefore, we cannot say that pedestrians who have higher SA score walk faster, and they finished their navigational tasks earlier than others.

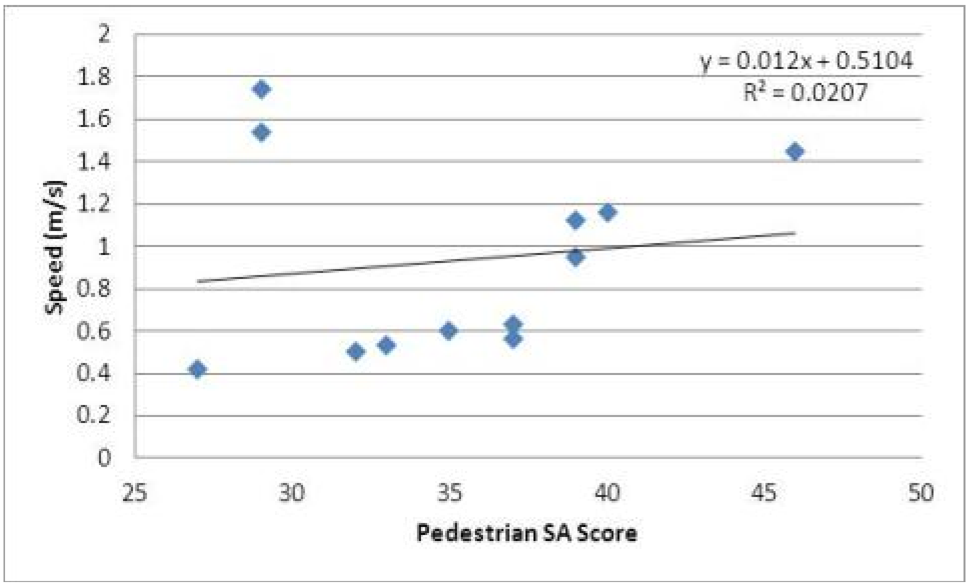

Figure 4.9 Speed as a Function of Pedestrian SA

Also, no strong association between SA score and the number of trajectory changes was found (r^2=0.23, F=1.32, p=0.28), which can be interpreted as people are more likely to change their speed rather than change trajectory.

Figure 4.10 illustrates the relationship between pedestrian SA score and individual zone of comfort (r^2=0.54). It shows higher SA score holders tend to maintain wider personal buffer zone to keep their current direction and desired speed as well as to avert collision.

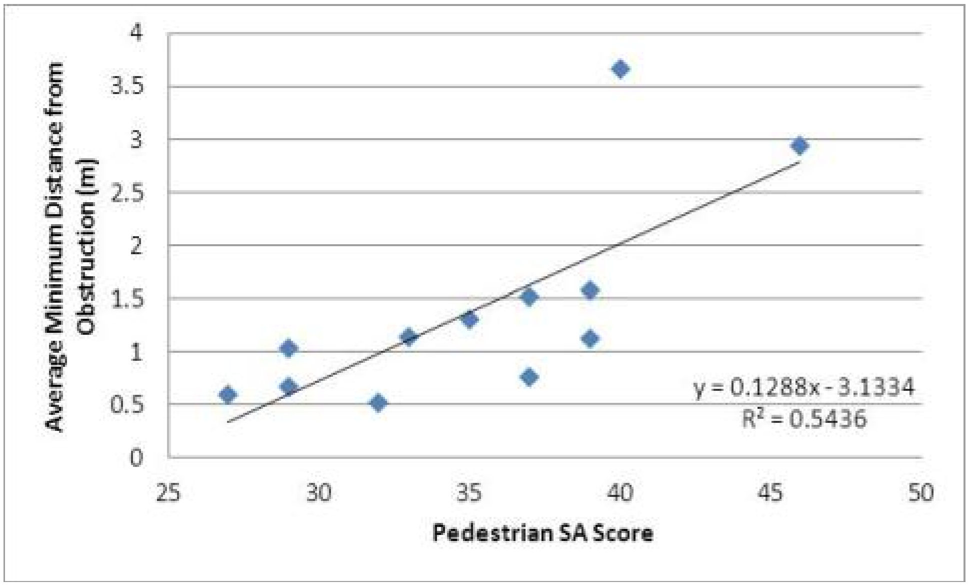

Figure 4.10 Pedestrian SA and Zone of Comfort

4.6.1.5 Facility Evaluation

The flow rate observed in the video footage was 1.03 ped/min/m and the pedestrian space was 26.87 m^2/ped. These measures are average instantaneous calculations. That is, they summarize the entire 20 minutes of footage analyzed considering each and every frame or instance. The high value for the pedestrian space is due to the fact that 68 pedestrians were in the region of interest over the entire 20 minute interval and the facility area was divided by the number of pedestrian observed in each frame to obtain average instantaneous pedestrian space across all frames for 20 minutes. If the video footage had shown crowded conditions, the pedestrian space would be much lower. These metrics can be used in evaluating the design of a pedestrian facility, with maximizing flow and comfort being the primary objectives. Additionally, it would be expected that the pedestrian space is a minimum threshold for human comfort.

One of the most common assessments of pedestrian facility design is level of service, as defined in the Highway Capacity Manual (TRB, 2000). The level of service of this particular corridor ranges from level A (based on flow rate and space) to level E (based on speed). This indicates that the width of the corridor is sufficient, but that the space allotment for each pedestrian may be lacking. The main reason that this particular corridor was poorly rated in average speed can be interpreted as a high occurrence of stationary movements and meandering. As a whole, it can be said that this corridor is wide enough for pedestrian navigation under usual circumstances. However, the utilization was poor at the time due to situational factors. Many pedestrians in the hallway were waiting to enter rooms, thereby decreasing utilization.

4.6.2 Field Experiments

After completing the empirical study under the constructed corridor setting, the recorded video footage from four surveillance cameras that contains participants walking behavior has been securely stored on an external hard drive. Abiding by IRB's regulation, research personnel who completed IRB training had an access to video footage and they coded footage to a set of numeric data with respect to each participant's location.

VirtualDub and ImageJ, open-source image processing tools, have been utilized to create image sequences from footage and to code images. Immediately after clicking any point on an image, it moves on to the next frame of image maintaining 0.1 second between two consecutive frames. When clicking, a middle point participant's feet that corresponds to his/her body axis has been considered as a participant's current location.

Since the coded data on location from the image sequence do not directly correspond to actual coordinate values, a coordinate conversion method was developed to convert image coordinate into real-world coordinate. On the site floor, totally 120 arbitrary and randomly selected locations (i.e., thirty points from each camera zone) in terms of x-y coordinate values were collected to fit the multiple linear regression models as appeared in equation (4.2). Parameters ($\beta's$) were estimated using stepwise method in order to predict real floor plan coordinate (x_{real}, y_{real}), and standard errors of estimates and coefficient of determinations can be found in the following table ($\alpha = 0.05$).

Table 4.6 Standard Error of Parameter Estimates and Coefficients of Determination for the Coordinate Conversion Model

	Camera 1	Camera 2	Camera 3	Camera 4
$SE(\hat{\beta}_{0x})$	0.0159*	0.0192	0.0307	0.0184
$SE(\hat{\beta}_{0y})$	0.0195	0.0175	0.0411	0.0152
$SE(\hat{\beta}_{1x})$	0.0000	0.0000	0.0000	0.0000
$SE(\hat{\beta}_{1y})$	0.0000	0.0000	0.0000	0.0000
$SE(\hat{\beta}_{2x})$	0.0000	0.0000	0.0000	0.0000
$SE(\hat{\beta}_{2y})$	0.0000	0.0000	0.0000	0.0000
R_x^2	1.000	0.999	0.998	0.999
R_y^2	0.999	0.999	0.997	1.000

Note: Unit of measure is in meter.

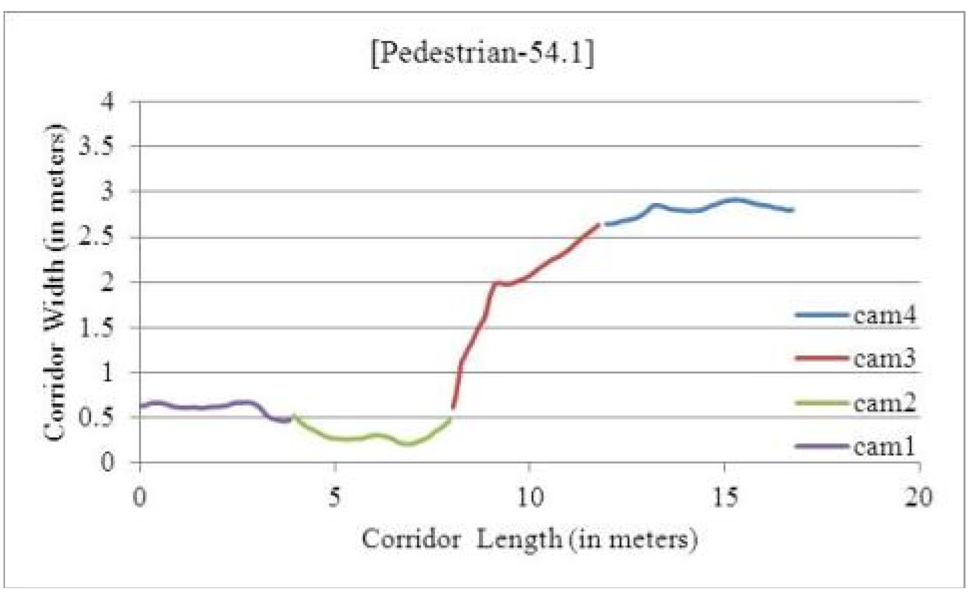

Figure 4.11 Realization of Pedestrian Trajectory with Footage from Each Camera

To inspect if the realized pedestrian density was matched to the planned one, both macro and micro level of pedestrian densities were determined as displayed in Table 4.7. Video footage was analyzed and density was calculated from both micro and macro viewpoints. Macro density is used to determine pedestrian space described in the HCM (TRB, 2000). This space can be obtained by measuring the sample area of the facility and determining the maximum number of pedestrians (i.e., macro density) at a given time, usually 10-15 minutes, in the walkway area. So it can be described as the peak number of pedestrians at a given time in the walkway area. Micro density indicates the average number of pedestrians in each frame.

The realized pedestrian densities for each scenario were deviated from the planned density levels or marginally corresponded to each range of space LOS grade in the Highway Capacity Manual (TRB, 2000). A subset of the empirical data that closely matched to the planned density level was selected to conduct statistical analyses as shown at the bottom of Table 4.7 and in Figure 4.12. When selecting a subset of data from the original data set, frame numbers whose density level most closely matched the planned density level (data within the red dotted boxes in Figure 4.12) were considered. As an example, the subset of data used for scenario 1 is shown within the red dotted boxes of Figure 4.12. Since the pedestrian space levels (either micro or macro level of pedestrian space) of the selected subset of the data fell within or marginally close to the range of planned space levels, the data subsets were deemed suitable for analysis with respect to density levels.

Table 4.7 Planned, Realized and Selected Pedestrian Densities

Planned		Realized						Selected					
Scenario	LOS	Density (Micro)	Space	LOS	Density (Macro)	Space	LOS	Density (Micro)	Space	LOS	Density (Macro)	Space	LOS
1	B	18.25	3.62	C	25	2.64	C	16.44	4.01	B	22	3.00	C
2	C	24.35	2.71	C	34	1.94	D	22.75	2.90	C	30	2.20	C
3	D	20.18	3.27	C	32	2.06	D	21.49	3.07	C	32	2.06	D
4	E	19.07	3.46	C	44	1.50	D	23.35	2.83	C	44	1.50	D
5	B	22.06	2.99	C	33	2.00	D	17.80	3.71	B	27	2.44	C
6	C	17.18	3.84	B	27	2.44	C	18.27	3.61	C	27	2.44	C
7	D	24.65	2.68	C	36	1.83	D	25.72	2.57	C	36	1.83	D
8	E	20.63	3.20	C	49	1.35	E	24.01	2.75	C	48	1.38	E
9	B	21.93	3.01	C	29	2.28	C	19.10	3.46	C	29	2.28	C
10	C	22.38	2.95	C	30	2.20	C	25.86	2.55	C	33	2.00	D
11	D	21.11	3.13	C	36	1.83	D	23.21	2.84	C	36	1.83	D
12	E	19.00	3.47	C	45	1.47	D	20.09	3.29	C	45	1.47	D
13	B	21.45	3.08	C	29	2.28	C	19.28	3.42	C	27	2.44	C
14	C	21.07	3.13	C	30	2.20	C	20.14	3.28	C	27	2.44	C
15	D	15.92	4.15	B	32	2.06	D	16.53	3.99	B	32	2.06	D
16	E	24.87	2.65	C	48	1.38	E	26.00	2.54	C	48	1.38	E
17	B	20.30	3.25	C	27	2.44	C	18.44	3.58	C	26	2.54	C
18	C	21.89	3.02	C	34	1.94	D	18.80	3.51	C	25	2.64	C
19	D	24.63	2.68	C	35	1.89	D	26.59	2.48	C	35	1.89	D
20	E	16.08	4.10	B	50	1.32	E	18.50	3.57	C	51	1.29	E

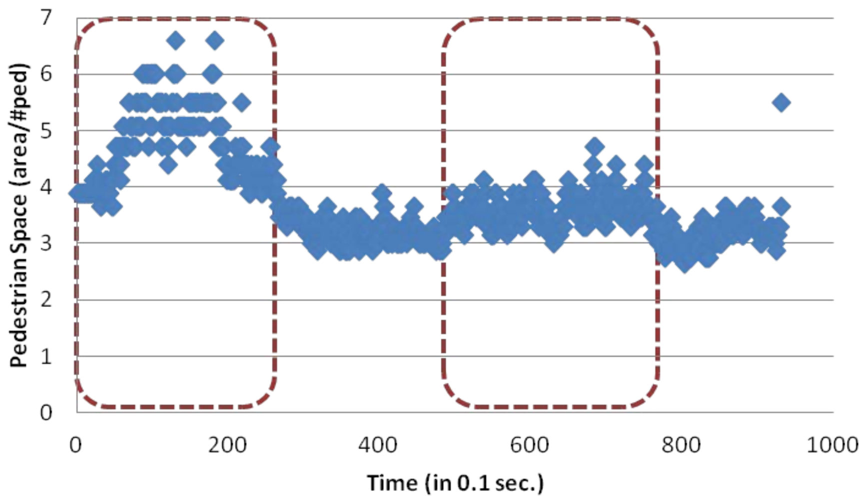

Figure 4.12 Selected Pedestrian Density for Scenario 1

A variety of measures were obtained to show the observed pedestrian behavior as displayed in Table 4.8. The observed overall average (standard deviation) walking speed, subjective walkability measure, and average minimum distance from obstruction (zoning hereafter as in Table 4.8) were 1.41 m/s (0.28), 14.28 (3.38), and 0.86 m (0.29) respectively. Male participants (1.43 m/s) walked faster than female (1.39) on average. The statistical designs incorporated a total of eight treatment combinations for uniflow and biflow mixture situation fixing speed level to normal as shown in Table 4.8, and 16 treatment combinations for all levels of each speed and pedestrian space.

Table 4.8 Descriptive Statistics for the Pedestrian Travel Behavior (N = 1000)

Gender	Speed Comb.	Space Level	# Flow	Speed Mean	Speed SD	Walkability Mean	Walkability SD	Zoning Mean	Zoning SD
Female	Normal	B	1	1.41	0.30	15.72	3.61	0.91	0.26
			2	1.44	0.11	11.36	3.80	0.80	0.28
		C	1	1.36	0.06	16.04	2.39	0.75	0.28
			2	1.39	0.06	11.88	3.97	0.86	0.28
		D	1	1.30	0.07	14.92	4.02	0.87	0.41
			2	1.43	0.09	10.84	3.76	0.83	0.24
		E	1	1.30	0.06	15.52	3.56	0.94	0.24
			2	1.29	0.08	11.40	3.45	0.96	0.21
	Slow - Normal	B	1	1.29	0.14	14.00	4.33	0.81	0.33
		C	1	1.19	0.11	16.20	2.18	0.88	0.27
		D	1	1.17	0.10	14.96	3.03	0.79	0.27
		E	1	1.08	0.17	15.20	2.77	0.86	0.35
	Fast - Normal	B	1	1.86	0.25	15.00	2.83	0.84	0.30
		C	1	1.61	0.15	13.40	3.89	0.74	0.29
		D	1	1.47	0.18	14.40	3.57	0.85	0.28
		E	1	1.51	0.14	14.33	3.97	0.95	0.43
	S-N-F	B	1	1.60	0.32	15.72	3.59	0.81	0.27
		C	1	1.38	0.27	14.56	3.88	0.85	0.29
		D	1	1.41	0.34	14.32	4.11	0.92	0.31
		E	1	1.27	0.27	13.52	4.28	0.79	0.29
		Female Overall		1.39	0.25	14.16	3.87	0.85	0.30

Table 4.8 (Continued)

Gender	Speed Comb.	Space Level	# Flow	Speed Mean	Speed SD	Walkability Mean	Walkability SD	Zoning Mean	Zoning SD
Male	Normal	B	1	1.50	0.11	15.48	2.08	0.94	0.26
			2	1.50	0.11	13.00	5.07	0.84	0.25
		C	1	1.41	0.04	15.84	2.44	0.86	0.32
			2	1.39	0.04	10.40	4.73	0.89	0.20
		D	1	1.35	0.05	15.36	2.63	0.98	0.21
			2	1.36	0.05	11.68	4.79	0.75	0.25
		E	1	1.22	0.06	16.76	1.48	1.03	0.32
			2	1.23	0.05	11.76	3.21	0.86	0.20
	Slow - Normal	B	1	1.47	0.16	13.16	3.21	0.69	0.33
		C	1	1.27	0.04	15.48	3.11	0.96	0.31
		D	1	1.17	0.10	14.76	3.03	0.83	0.38
		E	1	0.95	0.10	16.56	1.78	0.96	0.26
	Fast - Normal	B	1	2.15	0.18	15.48	2.00	0.78	0.24
		C	1	1.75	0.13	13.64	3.88	0.77	0.27
		D	1	1.49	0.12	14.60	3.74	0.89	0.28
		E	1	1.39	0.09	15.40	3.33	0.90	0.33
	S-N-F	B	1	1.99	0.23	15.96	3.09	0.77	0.25
		C	1	1.64	0.13	12.96	5.05	0.72	0.25
		D	1	1.37	0.15	15.33	3.31	1.03	0.26
		E	1	1.06	0.16	14.28	4.05	0.92	0.21
		Male Overall		1.43	0.30	14.39	3.80	0.87	0.29
Overall Gender				1.41	0.28	14.28	3.83	0.86	0.29

When participants walked under space level A, the measured average (standard deviation) walking speed, subjective walkability score, and zoning were 1.62 (0.33) m/s, 14.49 (3.72) points, and 0.82 (0.28) meters respectively. Other space levels were assigned and travel performances were also measured: for space level B, average (standard deviation) walking speed, subjective walkability score, and zoning were 1.44 (0.20) m/s, 14.04 (4.05) points, and 0.83 (0.28) meters respectively.; and when pedestrians walked under the space levels of C and D, the recorded performance measures with the same order of appearance as levels A and B were 1.35 (0.18) m/s, 14.11 (3.88), and 0.87 (0.29) meters for level C and 1.23 (0.20) m/s, 14.47 (3.68), and 0.92 (0.29) meters for level D.

The measured speeds (m/s) at each speed class, such as normal, slow-normal, fast-normal, and slow-normal-fast were 1.37 (0.13), 1.20 (0.19), 1.65 (0.28), and 1.47 (0.36) respectively. For walkability measure with the same order of appearance as speed, it showed 13.62 (4.13), 15.03 (3.13), 14.52 (3.47), and 14.58 (4.02). For zoning, measured values were 0.88 (0.27) meters, 15.04 (3.140 meters, 14.53 (3.47) meters, and 14.58 (4.02) meters respectively.

In regard to the number of pedestrian flows, participants walked in uniflow and biflow situations. When they walked in uniflow, the measured average speed, walkability and zoning were 1.42 (0.31) m/s, 14.96 (3.43), and 0.86 (0.30) meters. For biflow case, measured travel performance in the same order of appearance as uniflow, were 1.38 (0.11) m/s, 11.54 (4.14), and 0.85 (0.24) respectively.

4.6.2.1 Missing Data Imputation and Variable Transformation

The analysis of pedestrian travel behavior (i.e., observed walking speed, subjective walkability, and zoning) was conducted with four different aspects: data arrangement; factorial effects of space and number of flows; factorial effects of space and speed class; and impacts of spacing propensity on observed walking speed. Since the pedestrian data contained missing data points on participant weight (3.5 % of entire data), estimation of missing values using multiple imputation procedure was performed first.

Pedestrian travel performance data were imputed using Multiple Imputation and Markov Chain Monte Carlo procedures in SAS, and the imputed (i.e., on weight variable) prediction equation is reported in equation (4.6) ($F(4, 995) = 138.17$, $p < 0.0001$).

$$\widehat{Weight} = 146.58 + 36.44 Gender - 7.13 Speed + 0.15 Walkability - 3.52 ZOC \qquad (4.6)$$

Further analysis pertaining to participants' weight was performed using imputed data, and the weight variable was categorized into two levels, such that low level (less than median of weight) and high level (greater than median of weight) were created for analytical simplicity.

Since the variables did not hold assumptions linearity and homogeneity of variance, Box-Cox transformation was performed appropriately to minimize root mean squared errors. The obtained λ's for average speed, walkability, and zoning were -0.2, 2.0 and 1.2 respectively. Then these values were plugged into the Box-Cox power function to conduct statistical analysis appropriately. Tests of homogeneity of variance using Levene's method for speed (F (7, 392)= 2.13, p = 0.040), walkability (F (7, 392) = 2.25, p = 0.030.) and zoning (F (7, 392) = 1.94, p = 0.062) showed conducting ANOVA is reasonable at a significance level of 0.01 since F-test is very robust against ANOVA assumptions especially in a fixed effect model and equal sample sizes with a large sample size as the data this study explored (Kutner, et al., 2005).

4.6.2.2 Speed, Walkability and Zoning for each Space and number of Flows

Collected data were initially analyzed using two-way MANOVA, factorial arrangement of treatment in a randomized complete block design treating gender as a block. This analysis revealed significant multivariate effects for levels of pedestrian space and number of flow with respect to mean speed, walkability and zoning. Wilk's lambda for overall space and number of flow treatment combination was 0.41 (F (21, 1117.5) = 19.57, p < 0.0001).

Hierarchical (ordered) F-tests were conducted after rejecting the hypothesis of no overall multivariate effects. ANOVA resulted that space and number of flow interact to significantly affect mean speed ($F(3, 391) = 3.12$, $p = 0.026$) and mean zoning ($F(3, 391) = 2.83$, $p = 0.038$), but do not significantly affect mean walkability ($F(3, 391) = 1.12$, $p = 0.342$) as shown in Table 4.9. Both levels in number of flow were significantly different ($F(1, 391) = 147.84$, $p < 0.0001$) with respect to mean walkability. However, no significant difference in space ($F(3, 391) = 0.77$, $p = 0.513$) was found with respect to mean walkability. Also, no significant variations due to gender in speed ($F(3, 391) = 0.65$, $p = 0.423$), walkability ($F(3, 391) = 0.82$, $p = 0.365$) and zoning ($F(3, 391) = 1.20$, $p = 0.274$) were reported. Participants' body weight did not significantly affect mean speed ($F(1, 391) = 0.39$, $p = 0.5316$), mean walkability score ($F(1, 391) = 2.07$, $p = 0.1512$) and mean zoning ($F(1, 391) = 0.10$, $p = 0.7466$).

Table 4.9 Factorial ANOVA Results (p-values)

Dependent variables	Space	#Flows	Space*#Flows	Gender
Speed	**<0.0001**	**0.0027**	**0.0261**	0.4223
Walkability	0.5133	**<0.0001**	0.3419	0.3651
Zoning	**0.0335**	**0.0188**	**0.0382**	0.2742

Note: Bold values indicate significant findings (p-value < 0.05)

Average walking speed was not found to be affected by gender as shown in Table 4.9. Figure 4.13 shows the trend of speed in gender and results of multiple comparisons. The average (standard deviation) speed for female and male walkers were 1.37 (0.14) m/s and1.37 (0.12) m/s respectively. A post-hoc analysis using Fisher's LSD multiple comparisons showed that there were significant differences among all levels of space when pedestrians walked in uniflow. However, for biflow situation, no difference was found between space levels C and D unlike other space levels. The best walking environment combinations of number of flow and space level were space level B with both flow levels, that is, regardless of number of flow space level B provided best walking condition improving mean walking speed.

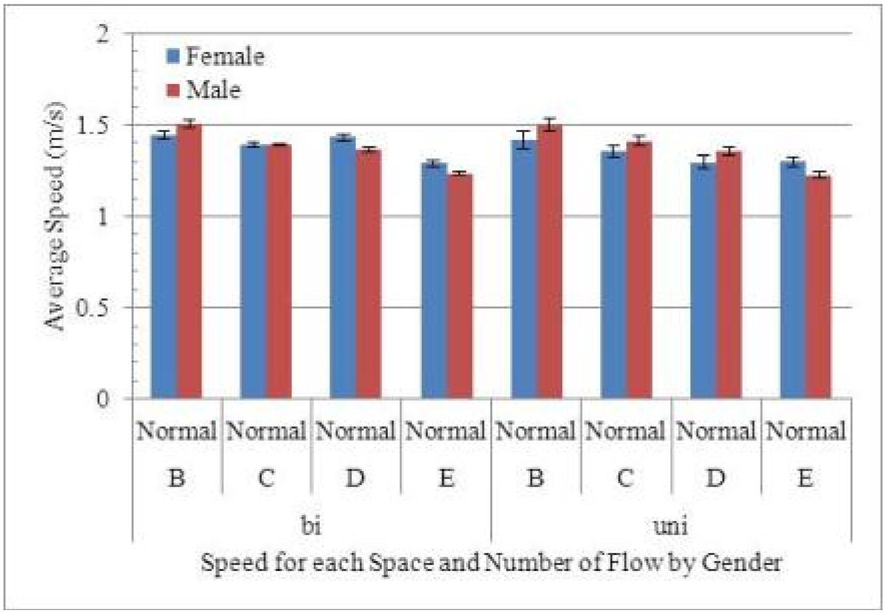

Figure 4.13 Speed by Gender based on Space and Number of Flow Combination (bars represent standard error of the mean)

The responded mean (standard deviation) walkability measures for female and male were 13.46 (4.13) and 13.79 (4.13). As revealed in factorial ANOVA result table, each space level did not affect mean walkability measure, but the number of flow significantly affected walkability meaning that pedestrians preferred to walk in the uniflow as shown in Figure 4.14. Variation due to gender was not significant.

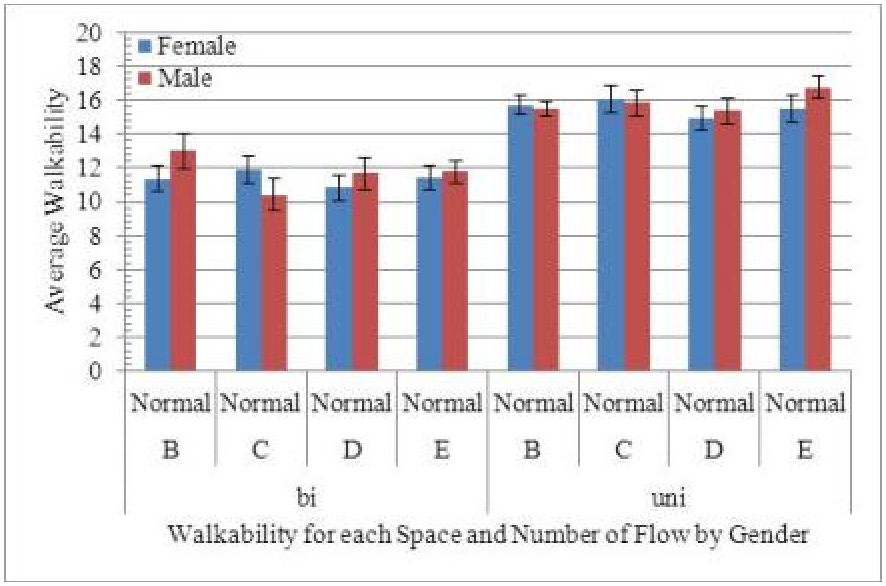

Figure 4.14 Walkability by Gender based on Space and Number of Flow Combination (bars represent standard error of the mean)

The reported average (standard deviation) minimum distance from obstruction for female and male walkers were 0.87 (0.28) and 0.90 (0.27) meters. As shown in Table 4.9, there was no variation due to gender as speed and walkability measures. However, mean zoning was significantly influenced by each level space and the number of flow. Figure 4.15 shows post-hoc analysis using Fisher's LSD multiple comparisons with respect to combinations of each level of space and the number of flow. For uniflow, there was no significant difference among space levels B, D, and E, but there was significant decrease in mean zoning when pedestrians walked under the space level C. When pedestrians walked in biflow, there was no significant change in mean zoning was found. For levels of space D and E, there were significant decreases in mean zoning when they walked in biflow directions; otherwise no significant change in mean zoning was found.

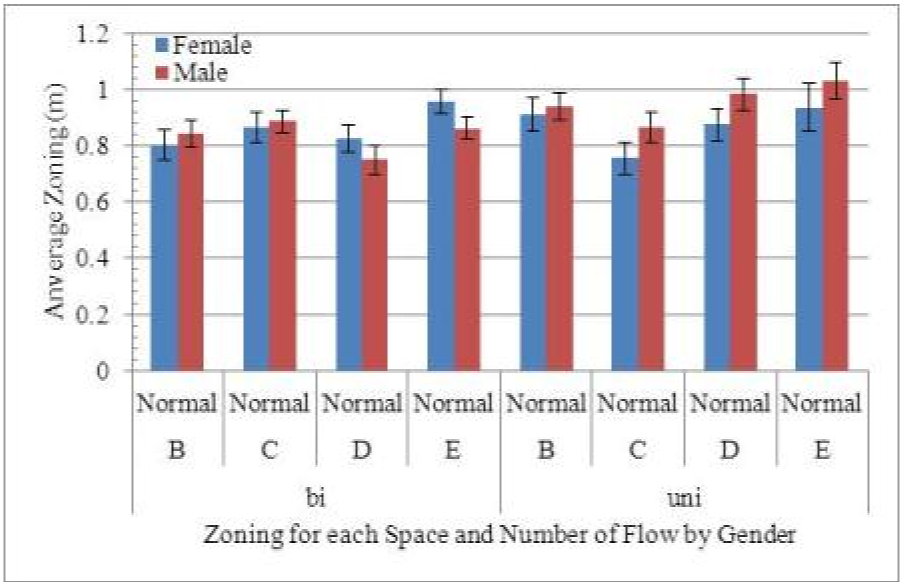

Figure 4.15 Zoning by Gender based on Space and Number of Flow Combination (bars represent standard error of the mean)

In order to investigate and identify the mathematically optimum conditions (environment settings) in pedestrian walking with respect to mean walkability, response surface modeling was conducted using response surface regression model with the method of least squares in SAS. A response surface model was obtained with a non-significant lack of fit to the data ($F(3, 392) = 0.70$, $p = 0.5499$) as illustrated in Figure 4.16. The perceived pedestrian walkability decreased as the number of flows increased from one to two, i.e., uniflow to biflow, with an approximate change in walkability of 5.5 points. Similar to the number of flows, the response surface showed that pedestrian space of A or B resulted in more preferable conditions for better walkability scores.

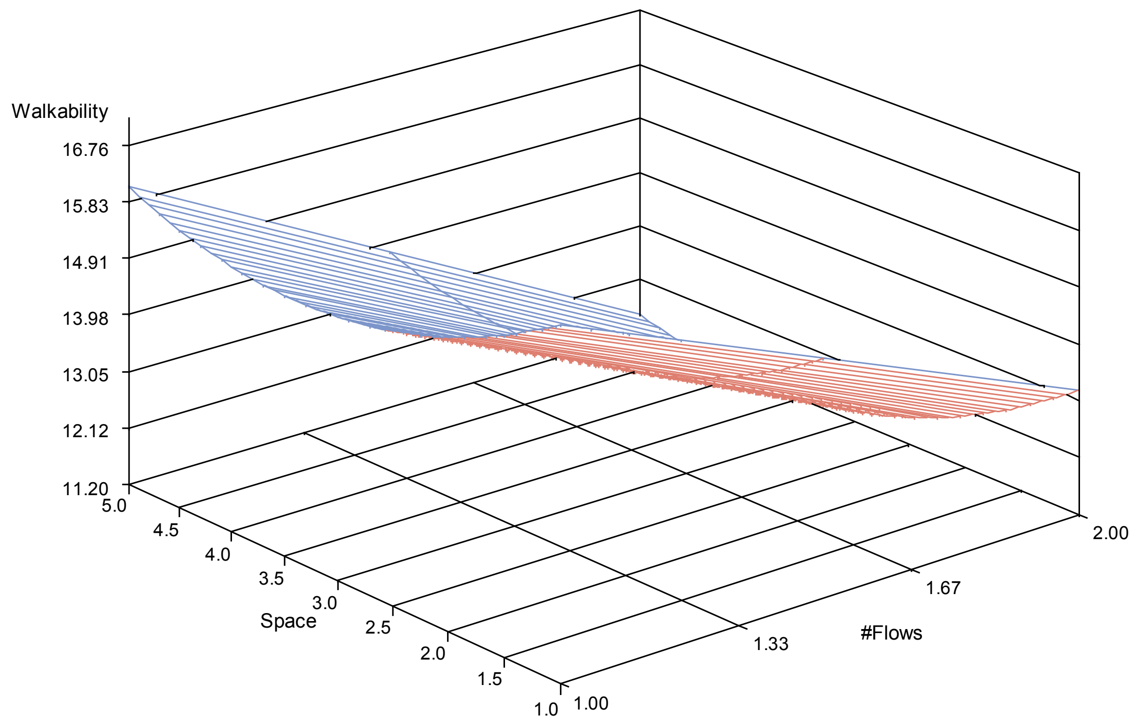

Figure 4.16 Fitted Response Surface as a Function of Space and Number of Flows

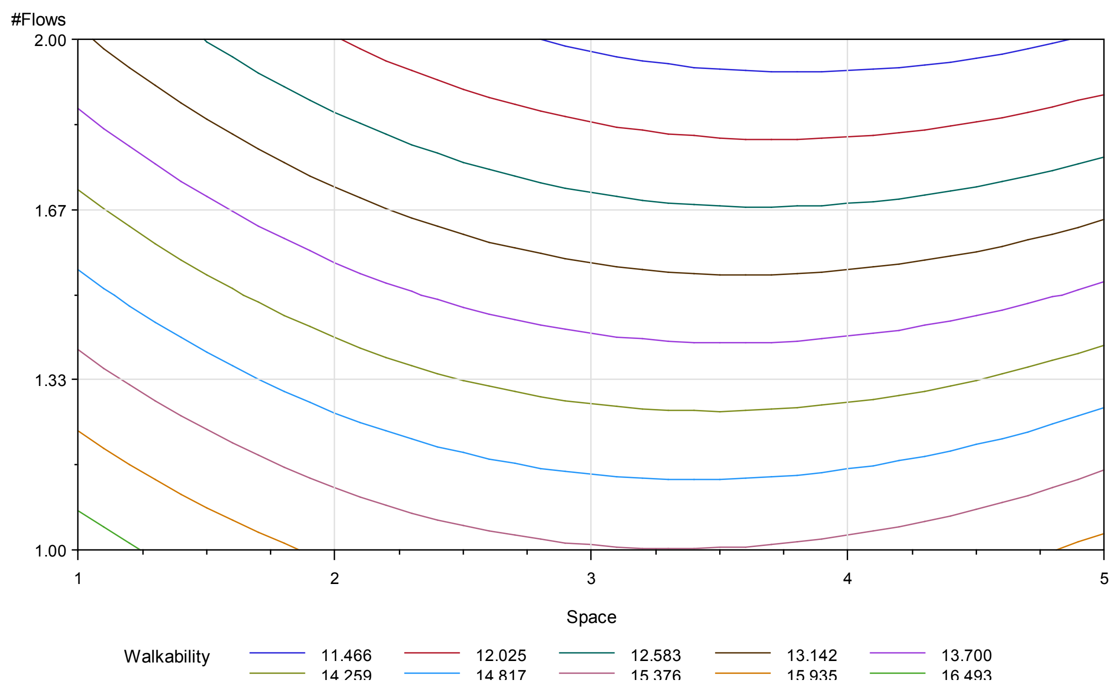

Figure 4.17 Contour Plot for the Fitted Response Surface

The contour plot in Figure 4.17 shows the optimum walkability score with the optimal combination of space and number of flows. The maximum walkability was 16.49 points (with a green line at the left bottom corner in the figure) with a space level of A and the number of flow of one.

Table 4.10 Means, Standers Deviations and Intercorrelations

			Intercorrelations				
Variable	Mean	SD	1	2	3	4	5
1.Efficiency	0.9785	0.0149	1.00				
2.Average speed (m/s)	1.3686	0.1291	-0.03	1.00			
3.Average zoning (m)	0.8804	0.2739	0.09	-0.07	1.00		
4.Min zoning (m)	0.4449	0.2813	**0.34****	0.04	**0.69****	1.00	
5.Walkability	13.6223	4.1283	**0.31****	**-0.11***	**0.14***	**0.23****	1.00

Note: N = 400.
Efficiency indicates the ratio of displacement (distance from start to end) to travel distance. Zoning means the measured minimum distance from obstructions (other pedestrians and both sides of corridor).
Bold values indicates significant findings (p-value < 0.05), *p < 0.01, **p < 0.0001.

To explore the relationship among measures, the correlation procedure in SAS was taken with a spearman option since some of variables were not normally distributed and estimating exact probability distribution for all variables were not possible. Some weak but significant correlations were found between efficiency and two measures (minimum zoning and walkability measures) as shown in Table 4.10. Unlike other significant relationship among measures, walkability was negatively correlated with average walking speed. Somewhat strong association between average zoning and minimum zoning was found since average zoning includes all pedestrian zoning behaviors even minimum zoning as well.

4.6.2.3 Speed, Walkability and Zoning for each Space and Speed Combination

The number of treatment combinations for space and speed class levels was 16 since both factors had four levels each to construct an arrangement of treatments for the experimental observation. An omnibus testing, a two-way MANOVA, was also conducted to test overall space speed class effects with respect to mean observed speed, responded walkability score and zoning (average minimum distance from obstruction). The analysis revealed significant differences across dependent variables. Wilk's lambda for overall space and speed class treatment combination was 0.34 ($F(45, 2320.9) = 22.82$, $p < 0.0001$).

Univariate ANOVAs were performed on each dependent variables of interest to assess the importance of the two factor interaction effects and main effects for the factors. The overall ANOVA results are given in Table 4.11. Hierarchical F-tests were conducted on the factorial effects starting from the interactions.

Table 4.11 Factorial ANOVA Results (p-values)

Dependent variables	Space	SpeedComb.	Space*SpeedComb	Gender
Speed	**<0.0001**	**<0.0001**	**<0.0001**	**<0.0001**
Walkability	0.5119	**0.0013**	**<0.0001**	0.5176
Zoning	**0.0003**	0.0585	**0.0044**	0.1468

Notes: SpeedComb indicates combination of asked walking speeds, such as slow-normal, normal, slow-normal-fast, and normal-fast.
Bold values indicate significant findings (p-value < 0.05)

ANOVA resulted that interactions between space and speed class significantly affected the mean speed ($F(9, 783) = 12.10$, $p < 0.0001$), mean walkability ($F(9, 783) = 3.99$, $p < 0.0001$) and mean zoning ($F(9, 783) = 2.69$, $p = 0.0044$). The auxiliary test for variation due to gender showed that it was significant only on mean speed ($F(1, 783) = 20.05$, $p < 0.0001$) while no significant variations due to gender on mean walkability (F

(1, 783) = 0.42, p = 0.5176) and mean zoning (F (1, 783) = 1.06, p = 0.3036) were reported. Also, variations due to participants' body weight were not significant with respect to mean speed (F (1, 783) = 0.84, p = 0.3594), mean walkability score (F (1, 783) = 0.00, p = 0.9802) and mean zoning (F (1, 783) = 1.06, p = 0.3036).

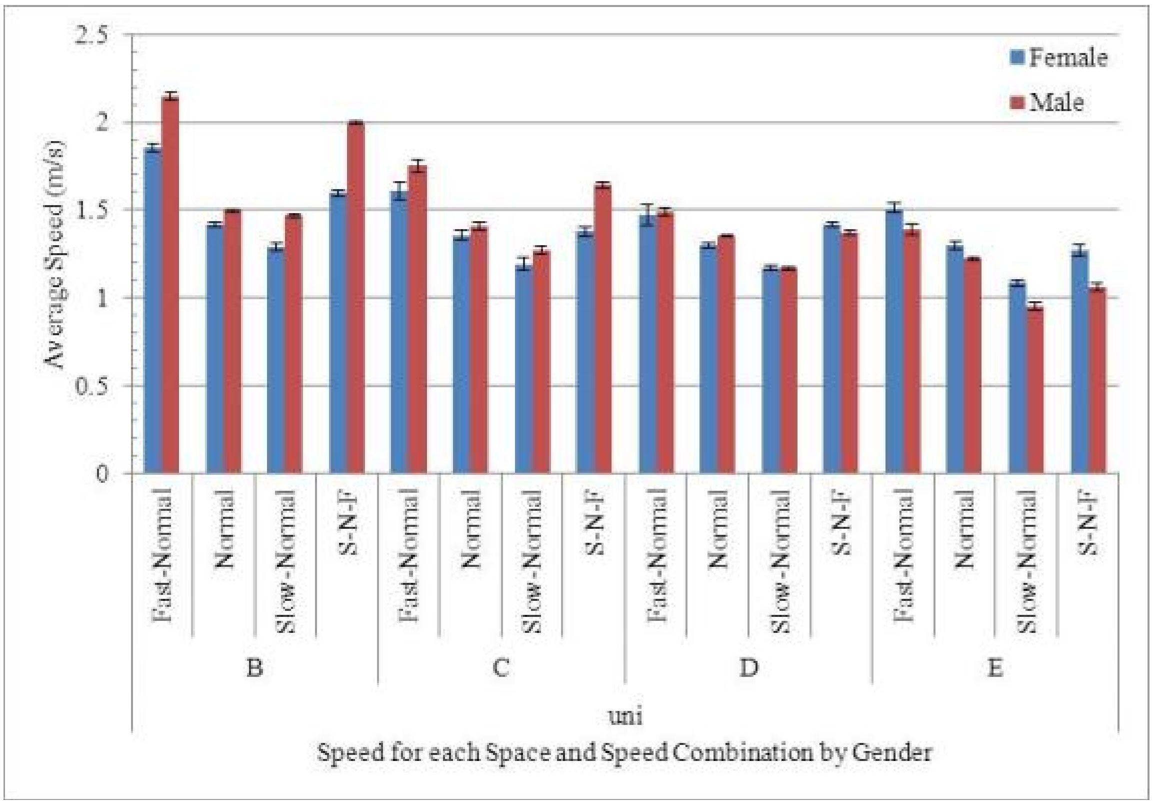

Figure 4.18 Speed by Gender based on Space and Asked Walking Speed Combination (bars represent standard error of the mean)

Figure 4.18 shows the trend of mean speed for each space level and speed level by gender. The average (standard deviation) speed for female and male walkers were 1.39 (0.27) m/s and 1.45 (0.33) m/s respectively. As displayed in Table 4.11, there was a significant variation due to gender on average speed. A post-hoc analysis using LSD multiple comparisons showed that there were significant differences across all levels of space and speed class, but no best treatment combination of space level and speed class level was found.

For each space class, when all participants walked at their own judgment of normal speed, there was a significant increase in walking speed as space level decreases from B to C. No significant change was found when other changes in space level. When the speed class was combination of slow and normal, there were significant increases in walking speed as space levels increase from E to D and from C to B. For speed combination of fast and normal, there were significant increases in mean walking speed as space levels increase from D to C and from C to B, but no significant change was found when space level increases from E to D. Regarding speed combination of slow, normal and fast, significant increases were reported for each space level increase.

For each space level, no significant change in mean walking speed was found only when the speed class changes from normal to slow, normal and fast combination. Otherwise, there were significant increases in mean walking speed for all other changes in speed levels.

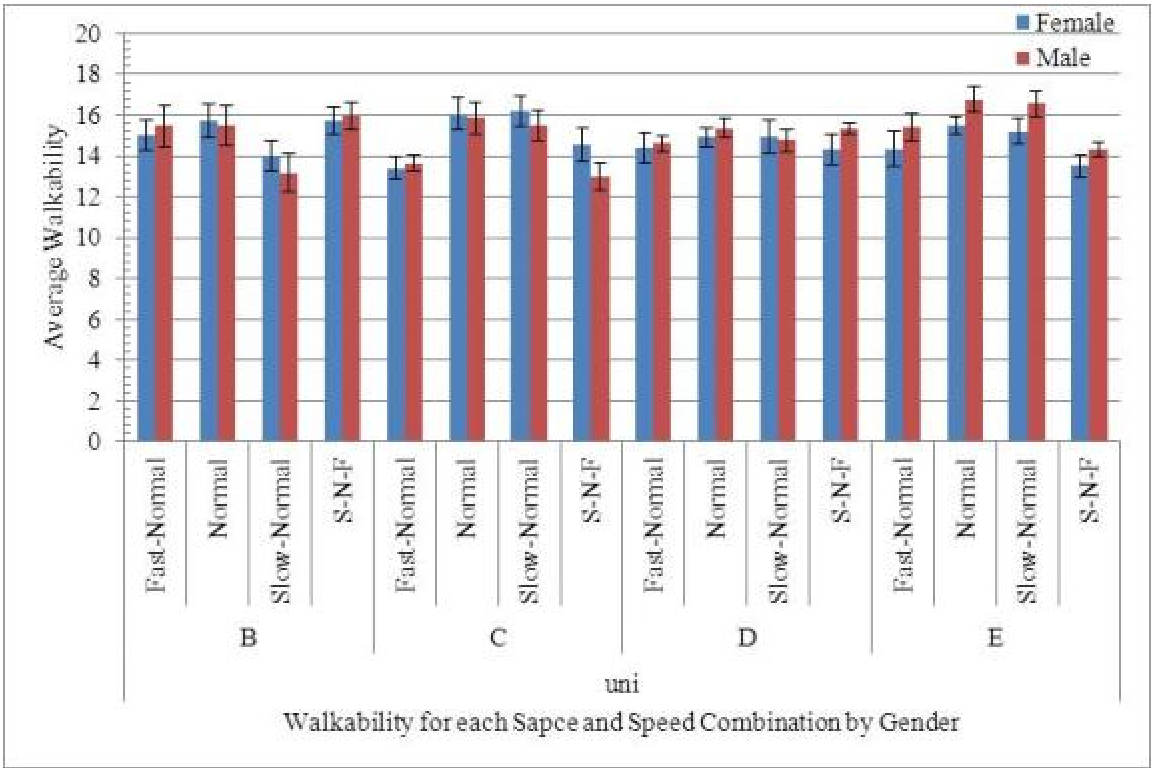

Figure 4.19 Walkability by Gender based on Space and Asked Walking Speed Combination (bars represent standard error of the mean)

The reported mean (standard deviation) walkability measures for female and male were 14.86 (3.58) and 15.07 (3.26) respectively. As revealed in factorial ANOVA result in Table 4.11, only speed class significantly affected mean walkability measure, but variation due to gender was not significant. For each speed class, there was a significant decrease in mean walkability only when the speed combination was slow and normal and space level changes from C to D. For single walking speed class of normal, there was no significant change in mean walkability score as space level changed. For speed class combinations of slow-normal-fast and normal-fast, significant increases in mean walkability were found only when space level increased from C to B.

For each space level, there were significant decreases in mean walkability score when speed class changed from normal to slow-normal-fast under space levels of E and

C. However, there was a significant increase in mean walkability score as speed class changed from normal to slow-normal-fast under space level of B. No best treatment combination of space and speed class was found that maximize mean walkability response, but multiple comparisons results showed slow or normal walking speed improve walkability for all space levels.

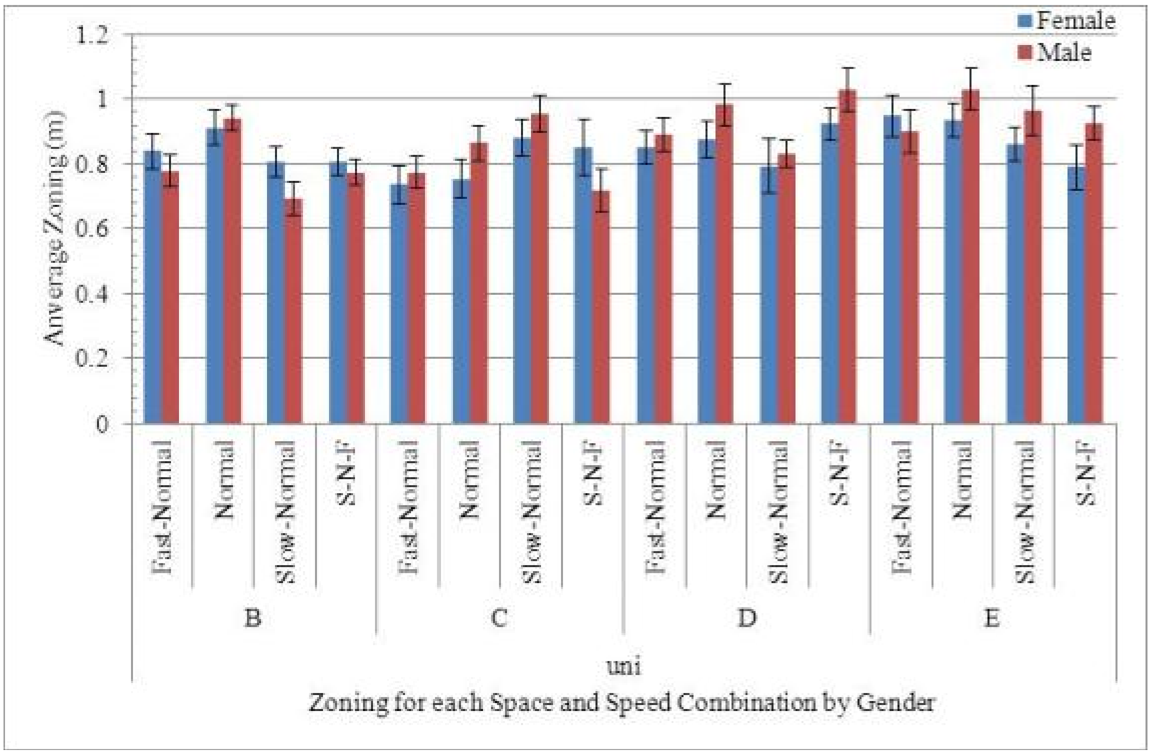

Figure 4.20 Zoning by Gender based on Space and Asked Walking Speed Combination (bars represent standard error of the mean)

The reported average (standard deviation) minimum distance from obstruction, i.e., zoning, for female and male walkers were 0.85 (0.31) meters and 0.88 (0.30) meters respectively. As shown in Table 4.11, no significant variation due to gender was found. Mean zoning measure was not significantly influenced by speed class either. Figure 4.20 shows pairwise comparisons for each level of space and speed class with respect to mean zoning measure. There were significant decreases in mean zoning measure when space level increased from D to C for speed class combinations of normal, slow-normal-fast and normal-fast. Also, mean zoning decreased significantly when space level increased from C to B for speed class combination of slow-normal. No significant change was found at all other space and speed class combinations. For space levels of B and D, there were significant increases in mean zoning only when speed class changes from slow-normal to normal. However, mean zoning measure was significantly decreased when speed class changed from normal to slow-normal-fast for space levels of B and E. Also, there was a significant increase when speed class changed from slow-normal to normal for space level of D.

A response surface model for mean walkability score was obtained with a non-significant lack of fit to the data ($F (10, 784) = 1.8362$, $p = 0.0510$) as illustrated in Figure 4.21. The perceived pedestrian walkability was good when all pedestrian walked at their normal speeds while mixed speed classes (e.g., slow-normal, fast-normal or slow-normal-fast) negatively affected mean walkability score. However, even though they walked at all different speed (slow-normal-fast), walkability score was high as long as pedestrian space was high enough (A or B). Generally, as space decreased walkability score decreased as well except the single normal walking speed. Walkability score was high under the congested situation when they were asked to walk at their normal speed only. The worst case was the combination of high pedestrian density and three different speed classes. The observed range of walkability score between best and worst cases was approximately 2.25 points, which was lower than the one obtained in the previous biflow case.

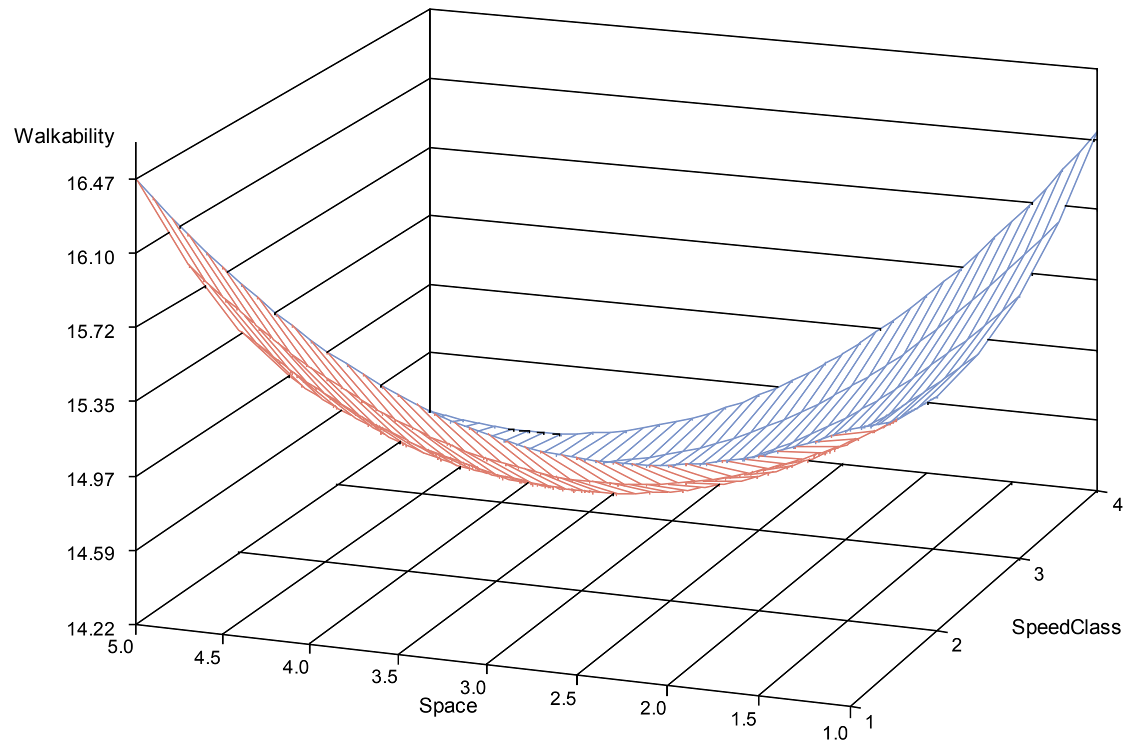

Figure 4.21 Fitted Response Surface as a Function of Space and Speed Class

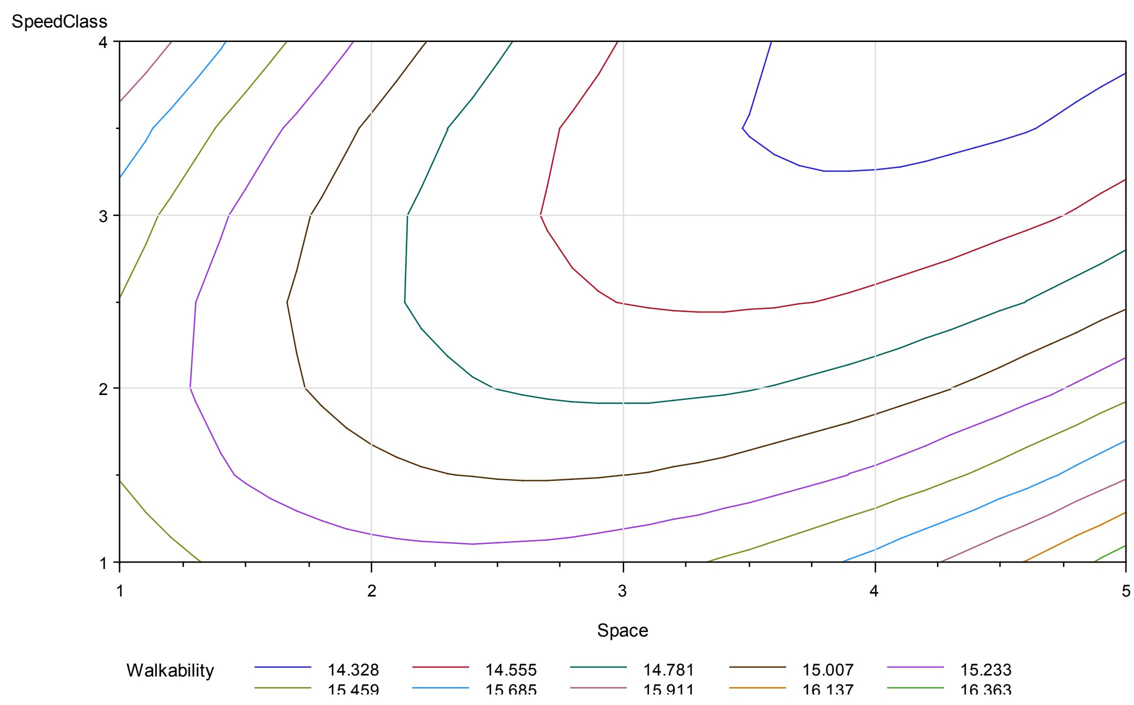

Figure 4.22 Contour Plot for the Fitted Response Surface

The contour plot in Figure 4.22 shows the optimum walkability score with the optimal combination of space and speed class. The maximum walkability was 16.47 points (with a green line at the right bottom corner in the figure) with a space level of D and a normal speed class.

Table 4.12 Means, Standers Deviations and Intercorrelations

Variable	Mean	SD	Intercorrelations 1	2	3	4	5
1.Efficiency	0.9758	0.0164	1.00				
2.Average speed (m/s)	1.4186	0.3049	**-0.41**	1.00			
3.Average zoning (m)	0.8631	0.3032	**0.15**	**-0.17**	1.00		
4.Min zoning (m)	0.4301	0.2839	**0.15**	**-0.20**	**0.71**	1.00	
5.Walkability	14.9632	3.4263	**0.14**	**-0.15**	**0.17**	**0.15**	1.00

Note: N = 800.
Efficiency indicates the ratio of displacement (distance from start to end) to travel distance. Zoning means the measured minimum distance from obstructions (other pedestrians and both sides of corridor).
Bold values indicates significant findings (p-value < 0.05) at p < 0.0001

Some weak but significant correlations were found among all measures as shown in Table 4.12. As reported in the previous case (number of flows and space levels were considered), average speed negatively correlated with zoning and walkability. Efficiency had a negative association with average speed, but stronger than the previous case. However, it had positive correlations with other measures. Walkability was also positively correlated with zoning.

4.6.2.4 Impact of Spacing Propensity on Observed Walking Speed

As reported in literature (Helbing & Molnár, 1997; Willis et al. 2002), pedestrians tend to maintain minimum distance from obstruction for their social and/or physical purposes while they walk in the public space. To investigate pedestrian spacing propensity under the controlled filed experiment setting, various pedestrian spacing measures obtained as displayed in Table 4.13.

Table 4.13 Means and Standard Deviations for Zoning and Speed

	Zoning (in meter)		Observed speed (in m/s)	
Spacing propensity	Mean	SD	Mean	SD
Zoning (wall)	0.7991	0.3197	1.4174	0.2774
Zoning (others)	0.9581	0.2063	1.4011	0.2782
Zoning (center)	1.0399	0.2370	1.3862	0.2729
Zoning (sides)	0.7701	0.2749	1.4236	0.2794

Note: Zoning (wall) and zoning (others) indicate the average distance from corridor wall and the average minimum distance from other pedestrians respectively.
Zoning (center) and zoning (sides) are defined as the average minimum distance from obstructions for those who walked center of the corridor and either side respectively.

Two-sample t-test showed that there was a significant different in zoning. Pedestrians kept more distance from other pedestrian than from corridor walls ($t(1998) = -12.09$, $p < 0.0001$). The obtained 95% confidence interval for mean difference in distance between wall and other pedestrians was (-0.4050, -0.2919). Also the difference between these groups with respect to mean speed was tested, and no significant difference was found ($F(1, 998) = 0.81$, $p = 0.3683$). However, a significant difference in mean speed between a group of pedestrians who walked center of the corridor and the other group walked either side of the corridor was reported ($F(1, 998) = 4.07$, $p = 0.0439$).

Table 4.14 Means and Standard Deviations for Travel Performance Measures based on Speed Rank

Measures	Speed rank	Mean	SD
Efficiency (displacement / distance)	Slow	0.9781	0.0294
	Normal	0.9772	0.0151
	Fast	0.9675	0.0310
Average Speed (m/s)	Slow	1.1606	0.1290
	Normal	1.3688	0.0436
	Fast	1.7048	0.2488
Average acceleration (m/s^2)	Slow	-0.0005	0.0059
	Normal	-0.0036	0.0085
	Fast	0.0013	0.0685
Average zoning (m) (overall)	Slow	0.8973	0.2934
	Normal	0.8793	0.2863
	Fast	0.8034	0.2885

The observed walking speed was ordered and categorized into three groups, such as slow, normal and fast, as shown in Table 4.14 to display means and standard deviations for each measure. Additional F-tests were conducted to investigate any differences in speeds with respect to mean zoning, mean acceleration and efficiency measures. It showed that at least one speed is significantly different with regard to mean zoning ($F(2, 997) = 9.91$, $p < 0.0001$) and mean efficiency ($F(2, 997) = 16.67$, $p < 0.0001$). However, no significant difference was found in speeds pertaining to mean acceleration ($F(2, 997) = 1.32$, $p = 0.2676$).

4.7 Discussion

The study take into consideration of both real-world observations and controlled field experiments on pedestrian behavior in order to collect microscopic pedestrian data, to quantify travel behavior, and to derive overall macroscopic characteristics using video footage. The foremost research question is how actually to extract the pedestrian data that contain physical and psychological characteristic so that the data can be arranged and analyzed appropriately. With the aid of image processing tools as described previously, video footage split into sequences of separate images and pedestrian data were coded from the image sequence as a format of x-y coordinate values. The image coordinate was converted into the real-world floor plan using the conversion equation as presented in equation (4.2) with parameter estimates. Coefficients of determination for the coordinate conversion models range from 99.7% to 100% meaning that 99.7% to 100% of total variations are explained by regression. However, errors still exist in the predicted value of constant terms. In other words, a standard errors of a constant terms in camera 1 were 1.59 cm for x-value and 1.95 cm for y-value, which means x-values could vary ±1.59 cm (3.18 cm in range) and y-values could also vary ±1.95 cm (3.9 cm in range).

The study includes four major hypotheses with minor ones for each major testing category. Basically, these research questions involves in identifying the factors or factorial interaction that affect the mean walking speed, mean minimum distance from obstructions, and mean perceived pedestrian walkability score. Also, the questions of interest include testing the effect of increasing the level of the factor on pedestrian measures being the same for all levels of other factor.

First, it was hypothesized that environment settings of pedestrian space level (i.e., space LOS grades B, C, D, and E) and the number of pedestrian flow directions (i.e., unidirectional and bidirectional flows) would affect pedestrian measures. Mean observed walking speed was significantly affected by the environment setting combination of pedestrian space and the number of flow directions. This supports the first major hypothesis and can be interpreted as both space and number of flows significantly influence on mean walking speed. The effect of increasing space level on mean speed depends on the number of pedestrian flows. When all pedestrians walk toward the same direction, an increase in space significantly increases mean speed. This is due to the fact as pedestrians have more space to manipulate their walking speed, especially to accelerate, they can reach their unimpeded free speed while walking. However, for each space level, an increase in the number of flow direction from unidirection to bidirection negatively impacts on mean speed as reported in literature (Daamen & Hoogendoorn, 2006; Daamen & Hoogendoorn, 2003) and mean walkability measure. When they find other pedestrians who walk in the opposite direction, they need to change their walking direction or walking speed to avoid potential collision (Strawderman et al., 2010), and they might feel uncomfortable. No matter what environment settings they are given, pedestrians tend to maintain minimum distance from obstruction (and more distance from other pedestrians) changing their walking directions or speeds more frequently.

The second question of interest is to invest the effect of physical walking component of speed class (all normal, combination of slow and normal, combination of fast and normal, and combination of slow, normal and fast equally likely). Tests resulted that speed combination significantly impacts on mean speed and mean walkability, and marginally affects the average minimum distance from obstruction with a p-value of 0.058. Also, the effect of speed combination on mean measures depends on change in pedestrian space level. For each speed combination, mean walking speed increases as pedestrian space increases as discussed in the previous research question. The best combination of space and speed class is space LOS B (the highest one in the study configuration) and speed combination of normal and fast (the fastest speed combination here) with an average (standard deviation) speed of 2.0025 (0.2584) m/s. No variation due to gender was found with respect to walkability and zoning, except speed (Lee et al., 2009; Lee et al., 2008). Male walked faster than female unlike literature (Daamen &

Hoogendoorn, 2006; Fitzpatrick et al., 2006; Bierlaire et al., 2003) since participants were asked to complete their tasks as described on their task information card (Figure 4.1) as well as male participants might have potential physical vigor. An effect of body weight was also tested and it resulted in no significant variation due to weight due to the fact that participants can be categorized into young group with a mean age of 21.4 years and a mean weight of 171.98 lbs. Therefore, hypotheses regarding no gender and weight effects on walkability and zoning were supported.

Pertaining to pedestrian zoning characteristic numerous terminologies have been employed to describe pedestrian spacing. Fruin (1997) pointed out that there is a certain degree of distance from obstruction for comfortable walking, called zone of comfort. Other jargons that contain similar meaning to zoning are territorial effect (Bierlaire & Antonini, 2003), social force (Helbing & Molnár, 1997), and personal distance (Hall, 1966). Then how far do pedestrian tend to keep distance from other pedestrians or obstacle? And how does pedestrian spacing propensity impact on pedestrian travel performance? The third major research question involves the investigation of role of a zoning factor, and it was assumed that pedestrian spacing propensity (Table 4.13) would affect observed mean walking speed and perceived walkability score.

The study found a significant difference in the minimum distance from other pedestrians and the minimum distance from corridor wall (either side); and a significant difference between these groups with respect to mean walkability score (not significant in mean speed). It shows people are likely to keep more distance from other pedestrians than from corridor wall, and pedestrians who walk close to corridor wall (keeping more distance from other people) have higher walkability score. This proves pedestrians have their own social distance to some extent and they feel more comfortable when the distance is secured (overall, 0.86 m). Pedestrian zoning explains people tend to highly value spacing rather than speed under the usual walking situation.

Another spacing characteristic of walking center of the corridor and walking either side was taken into consideration. There was a significant finding with respect to mean speed, but not mean walkability, between a group walked center of the corridor and the other group walked side of the corridor. This finding confirms the statement that pedestrians prefer to walk side of the walkway to maintain current speed and to avoid collision (Helbing & Molnár, 2001). It revealed that people who walk either side of the corridor have higher speed than those who walk center of the corridor, which supports the third research hypothesis and is coherent to findings in literature.

The last hypothesis for the study was to explore the association among variables, and it assumed that travel performance measures would be correlated with walkability. There were weak but significant correlations between walkability and efficiency, speed, acceleration, and zoning (Table 4.13, Table 4.14). Therefore, the research hypothesis is supported. However, even though most variables have significant association among them with weak to moderate correlation of coefficients, just developing a fitted (predicted) equation of travel performance (e.g., mean speed) to the data may not be appropriate since a weak or moderate correlation of coefficient would be statistically significant with samples in excess of 700 (O'Rourke et al., 2005). To resolve this issue and obtain mathematically optimal level of factorial combination (preferable walking conditions in reality) for maximum pedestrian walkability, quadratic response surface models to the data were developed with statistically insignificant lack of fit

4.8 Conclusion and Future Work

In the study, a framework to quantify pedestrian traffic behavior, and analyze physical and cognitive behavior from the real-world observation and field experiment was presented. Data collection methods pertaining to the plan of an empirical study site, non-intrusive way of communication with participants between trials, and data coding and conversion from video footage to numeric information for further statistical analyses were presented. Walkability survey questionnaire was also developed to quantify pedestrian comfort, performance and satisfaction in walking.

A select number of pedestrian behaviors from the behavioral study were analyzed. The focus of the analysis has been on pedestrian speed, zoning and walkability. The overall average speed, zoning distance and walkability score were 1.41 m/s, 0.86 m and 14.28 points (out of 21 points) respectively. This study presents unique findings in regard to pedestrian behavior. The quantification of zoning and walkability is an important step to understanding the spacing of pedestrians, capacity of facilities, and friendliness of environment. It allows to us see pedestrians' preference in choosing center/side of the corridor and tendency in keeping their own personal distance from other pedestrians and obstacles. It also demonstrates high pedestrian walkability is maintained as long as preferred personal distance is secured regardless of pedestrian density. The types of empirical data presented are not readily found in literature. It is important that further behavior studies be conducted to strengthen this body of work.

Future studies are planned to be conducted in intermodal facilities to gather additional information concerning pedestrian traffic in a variety of corridors. The goal is to identify common patterns of behaviors among pedestrians and to distinguish the pedestrians' characteristics that contribute to their behavior in traffic under various conditions. These studies will provide the data needed to improve the behavioral models incorporated within the pedestrian simulator that is undergoing.

Survey reliability and validity pertaining to walkability assessment has not been rigorously investigated. Though reliability and validity are likely to be both sides of a coin, which is somewhat hard to improve simultaneously, more factors in the literature that impact pedestrian walkability will be considered putting careful wording, format and content to reduce significant subject's own unreliability and invalidity of survey items.

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CHAPTER V

ANOHER LOOK AT PEDESTRIAN LEVEL OF SERVICE

5.1 Abstract

The assessment of pedestrian facilities is examined through pedestrian level of service (LOS) criteria. Although there are existing LOS metrics used in the transportation field today, they do not address all of the factors that we have found to impact a pedestrian's facility usage. The current Highway Capacity Manual (HCM) methodology for assessing pedestrian LOS over-simplifies the pedestrian traffic situation, and generalizes conditions with the overall average traffic performances within a certain period of time. Pedestrian traffic conditions are not simple enough to determine facility service level with the existing HCM methodology. In this study, adhoc and tailor-made metrics are presented for more realistic service level assessments, which may provide practical improvement points in facility design with great efficiency and less loss of goods. The proposed methodologies are composed of space revision LOS, delay-based LOS, preferred walking speed (PWS)-based LOS, and 'blocking probability' with simple operational examples from case studies. Future work pertaining to improving the performance of revised LOS is presented.

Keywords: level of service, spatial behavior, delay, preferred walking speed, blocking

5.2 Introduction

Level of Service (LOS) is often used to evaluate the performance of pedestrian facilities, determine the need to redesign them and analyze the efficiency of them after proposed changes and development in facility design. Existing pedestrian LOS studies are categorized into physical and psychological aspects. A physical study is focused on overall average speed, pedestrian density and flow rate while the psychological study mainly deals with environmental factors that have impacts on pedestrian LOS. Highway Capacity Manual (HCM) (TRB, 2000) describes the most commonly used methodology for the physical component of LOS assessment criteria. The previous and current versions of the HCM are based on pedestrian behavior research from Fruin (1971), Millazo et al. (1999) and Rouphail et al. (2000). Pedestrian LOS as defined in the HCM (Table 5.1) provides a standardized method for pedestrian traffic analysis in the United States. The HCM also provides instruction on data collection needs, methods, and analysis. While the HCM LOS provides a general framework for traffic analysis, it does not include many aspects of pedestrian traffic characteristics that impact LOS, such as instantaneous speed and some psychological factors. While this is not necessarily incorrect, there are a number of factors involved in pedestrian movement that are not considered, thus making it incomplete.

Many shortfalls of the current HCM LOS methodology exist. Pedestrian flow characteristics could differ as a function of location (e.g., metropolitan area, transportation facility, shopping mall, etc.). Pedestrians are likely to change their walking behavior and perceptions based on the heterogeneous environmental characteristics surrounding them. For instance, if a group of people with multiple personal items were frequently observed in this location, the average speed and personal spacing could be different from other locations. The difference in walking characteristics between locations requires a different service quality measurement and rating scale for each location.

Preferred spacing is not addressed. Pedestrians have their own preferred minimum distance from obstacles and other pedestrians. More specifically, this minimum distance is impacted by type of obstruction (outdoor vs. enclosed corridor; moving vs. stationary obstruction), as well as pedestrian density.

Multiple pedestrian flow directions and densities are not accounted for. It is possible that a pedestrian stream varies its physical form due to an opposing predominant stream. Therefore, there is a need to incorporate the impact of multiple flow directions on pedestrian flow rate and speed (or delay), so as to encompass the reduction in capacity phenomenon comparing balanced flow and unidirectional flow.

HCM LOS assumes all pedestrians are equal, though personal characteristics heavily influence walking behavior. Pedestrian traffic characteristics could be time and space dependent. To include these characteristics, it is necessary to conduct microscopic pedestrian traffic measurement based on both temporal and spatial data collection scheme (e.g., peak time, non-peak time, time of the day, day of the week, and location). The HCM LOS rating scale was calculated based on a macroscopic view of pedestrian traffic with a 15 minute observation timeframe, such as overall travel speed, density, and flow rate.

Table 5.1 Pedestrian Walkway Level of Service (TRB, 2000)

LOS	Space		Flow Rate		Average Speed		v/c* ratio
	(m^2/ped)	(ft^2/ped)	(ped/min/m)	(ped/min/ft)	(m/s)	(ft/min)	
A	$\geq$5.6	$\geq$60	$\leq$16	$\leq$5	$\geq$1.3	$\geq$255	0.21
B	3.7-5.6	40-60	16-23	5-7	1.27-1.30	250-255	0.21-0.31
C	2.2-3.7	24-40	23-33	7-10	1.22-1.27	240-250	0.31-0.44
D	1.4-2.2	15-24	33-49	10-15	1.14-1.22	225-240	0.44-0.65
E	0.75-1.4	8-15	49-75	15-23	0.75-1.14	150-225	0.65-1.00
F	$\leq$0.75	$\leq$8	variable	variable	$\leq$0.75	$\leq$150	variable

Note: v/c* indicates volume to capacity ratio.

Recent researches on pedestrian LOS report that there are numerous environmental or psychological factors that interact with LOS metrics. There are some prevailing LOS methodologies to evaluate a pedestrian facility in this category, such as time-space analysis, regression model of pedestrian LOS, conjoint analysis' and categorical analysis. Benz (1986) suggested a time-space based approach that includes pedestrians' travel agenda or trip purpose. The amount of time-space available is determined by subtracting the time-space required from the total time-space available (m^2*min) according to a travel agenda. The resulting value is then divided by the total navigation time (ped*min) to obtain a space metric for the pedestrian facility. The time-space method is useful in that it takes into consideration a pedestrian's travel agenda and it is easy to implement since it only requires macroscopic traffic performance data and employs existing HCM space category metrics. However, it cannot be used in a pedestrian facility with different trip purposes, as the time required for various activities may differ. To perform an analysis, the observation of detailed behavior is necessary based on predetermined types of trip purposes. This method is a type of mesoscopic way of analysis. Most of pedestrian LOS research has mainly focused on traffic performance (e.g., speed, density and flow rate), while some studies have been performed in the light of the fact that what pedestrians experienced or how they felt regarding safety and comfort of pedestrian facility when navigating.

Philips et al. (2001) presented a way of evaluating roadside walking condition. Participants were used to evaluate the walking condition of their environment as they navigated the predetermined segment of the path. Both safety and comfort factors were assessed on a 6-point Likert scale ("A" is the safest and most comfortable). Investigators identified LOS factors while they observed participants. Based on the factor scores (maximum of 6) of participants and LOS factors determined by investigators, they developed a regression model for pedestrian LOS. This method is easy to apply as well, but defining LOS factors is not an easy job, as well as there is no indication of what constitutes a reasonable number of LOS factors to use as explanatory variables.

There have been researches to identify psychological factors as described previously. The factors not included in researches were recognized and categorized using conjoint analysis based on the relative importance of factors, which is weighted utility, to pedestrians (Muraleetharan et al., 2004). They generated eight attributes with three levels across the attributes, and distributed questionnaires to the sampled participants. The weighted utilities were determined for sidewalk and crosswalk settings, which yielded the scale ranging from zero to ten ("10" is the most preferred walking condition). Identifying factors with degree of importance that pedestrian felt is useful since this method is based on perceived walking experience, which means pedestrian subjects were familiar with the area. However, it may contain participants' biases when answering each question, and is somewhat too much microscopic because this approach is merely based on participants' responses without considering actual traffic performance analysis.

Dixon (1996) presented categorical pedestrian LOS analysis that provides the evaluation criteria. She hypothesized that there is a critical mass of variables that present in pedestrian facility to attract walkers. The criteria encompass provision of basic facilities, conflicts, amenities, motor vehicle LOS, maintenance, and multimodal provision, which constructs the scoring system raging from one to 21. Dixon's method is a well structured rating system and offers a comprehensive definition of LOS that gives LOS grades from A to F with descriptions of what rating criterion (and sub-elements) applied. This method can be better used when including quantitative measures of effectiveness because it considers more qualitative factors.

In this study, microscopic traffic performance measures have been used to identify interactions between pedestrians and their environment that encompass a revision of pedestrian space, include an instantaneous delay metric, and take into account the ratio of preferred walking speed to instantaneous speed. A macroscopic measure of blocking probability is also discussed.

5.3 Revised LOS Assessment Methodology

The adjustment of LOS began with identifying factors that potentially affect existing HCM LOS criteria under uninterrupted traffic situations. Three factors have been found in the literature: (1) pedestrians' preferred minimum distance from obstruction (TRB, 2000); (2) pedestrian delay (Bloomberg & Burden, 2006); and (3) pedestrian queue and blocking (Cruz & Smith, 2007; Cheah & Smith, 1994). These factors were taken into consideration when revising the space LOS in the HCM and developing other LOS methodologies that are not in the current HCM LOS criteria. Also operational examples were provided to show the mechanism of methodology in a simple way using empirical data in Strawderman et al., 2010 and Lee et al., 2008.

5.3.1 Spatial Reduction in Walkway Capacity

One of the most important measures of effectiveness for the pedestrian facility is space. It has been noted that walkway density impacts flow rate and speed when the density exceeds a certain threshold (Fruin, 1971; TRB, 2000). Even an individual's preferred minimum distance from obstruction in a certain location may impact his/her use of space (Bloomingburg & Burden, 2006). People who have a longer preferred minimum distance from obstruction would tend to use a pedestrian facility ineffectively in order to ensure their preferred distance (see section 4.6.2.). Moreover, when pedestrians are faced with the counter-flow of other pedestrians, the observed walkability, zoning (section 4.6.2) and speed (Bloomingburg & Burden, 2006) are affected. These phenomena are due to that fact that there are impacts of opposing volume friction force (Bloomingburg & Burden, 2006) that decreases speed and increases preferred minimum distance from obstruction (Matsushita & Okazaki) in terms of spatial economy. In this case, the LOS grade determined using traditional measures would be higher than the one actually experienced or observed since the HCM LOS criteria give overall grades without considering personal psychological distance (e.g., preferred minimum distance from obstructions). Also, there is reason to believe the phenomena may cause similar reductions in walkway capacity in pedestrians' mind (Bloomingburg & Burden, 2006).

When pedestrians walk in a corridor with their own preferred minimum distance from obstruction, they are likely to keep the distance from the wall as well. Based on observation, this distance (around 0.8 m, Lee et al., 2008 and section 4.6.2) has never been used from the beginning till the end of their navigation. This may be a safe and comfort use of walkway, but not efficient or economical. The HCM LOS provides rating criteria regardless of this psychological issue, so it is proposed a virtual reduction in corridor width to apply the HCM LOS while accounting for the phenomena described previously and calculating the actually observed LOS assuming that this distance reflects pedestrians' propensity to maintain minimum distance from obstructions. In other words, a reduction in corridor width could be practical while determining corridor capacity and pedestrian density since pedestrians who keep their distance from obstruction could feel the corridor width narrower than the actual dimension.

This approach is applicable if the average minimum distance is greater than the personal comfort zone (0.54 m in radius) proposed by Fruin (1971) because it was used to construct a pedestrian body ellipse for designing purpose in the HCM. If the average minimum distance is less than the personal comfort zone, the effect of personal zoning is relatively negligible and the corridor simply has higher pedestrian density. Therefore, space adjustment is not necessary. If, however, the average minimum distance is greater than the personal comfort zone, the observed LOS grade could be lower than the grade calculated using the HCM LOS method due to exclusion of average minimum distance from obstruction. Some equations are used to determine the average instantaneous minimum distance from obstruction. Let $d_{i,i'}(t)$, $d_{i,wall}(t)$ and $\min_t \left\{ d_{i,i'}(t), d_{i,wall}(t) \right\}$ be the distance from other pedestrians in the frame, distance from wall in the frame, and minimum distance from obstruction and wall in the frame respectively. The equations applied are:

$$d_{i,i'}(t) = \sqrt{(x_i - x_{i'})^2 + (y_i - y_{i'})^2}, \quad \forall i, i' \text{ in each frame t } (i \neq i'); i = \text{pedID} \qquad (5.1)$$

$$d_{i,wall}(t) = \sqrt{(x_i - x_{wall})^2 + (y_i - y_{wall})^2} \tag{5.2}$$

Then, average minimum distance from obstruction (AMD) can be obtained using the following equation:

$$AMD = \frac{1}{T}\sum_{t=1}^{T} \min_t \left\{ d_{i,i'}(t), d_{i,wall}(t) \right\},\ T = \text{total number of frames.} \tag{5.3}$$

The detailed adjustment procedure for the walkway capacity is given by:

1) Calculate AMD
2) If the determined AMD is less than the personal comfort zone (PCZ), stop and apply HCM LOS; otherwise go to step 3).
3) Reduce walkway width by the difference by the difference between observed AMD and PCZ.
4) Recalculate the capacity (area) of walkway with the modified walkway width.
5) Calculate rate of change, which is given by [1 + |change in capacity / original capacity|].
6) Rescale LOS space category multiplying the rate of change in step 5) by the existing space category in HCM LOS.

5.3.1.1 Operational Example

The dimension of the selected site was 3 m (10 ft) * 24 m (79 ft) with an area of 72 m^2 (794 ft2). The observed AMD from obstruction was 0.85 m. The adjustment procedure follows:

1) AMD = 0.85 m
2) AMD > PCZ; adjustment required, continued to step 3

3) Adjusted width = Walkway width – (AMD – PCZ) = 3 – (0.85 – 0.54) = 2.69 m
4) Modified walkway area = 2.69 m * 24 m =64.6 m^2
5) Rate of change = [1 + {(72 – 64.6) / 72}] = 1.1
6) For instance, level A was rescaled by multiplying 5.6 by rate of change (1.1), providing a new value of 6.16.

The example dealt with the case that the average minimum distance is greater than the personal comfort zone. In this situation, pedestrians required more space than is needed for limited comfortable circulation, which means they consumed more space than usual (i.e., inefficient uneconomical use of walkway). That is to say, the actually observed LOS grade could be lower than the grade calculated using the HCM method due to exclusion of average minimum distance from obstruction. Therefore, additional space (e.g., body ellipse and additional space) should be taken into account for the practical facility service level assessment. The modified LOS table for pedestrian space is displayed in Table 5.2:

Table 5.2 Modified LOS Rating Scale for Space

LOS in space	Before (in HCM) (m^2/ped)	After (proposed) (m^2/ped)
A	≥5.6	≥(5.6 * 1.1)=6.1
B	3.7-5.6	4.1-6.1
C	2.2-3.7	2.4-4.1
D	1.4-2.2	1.5-2.4
E	0.75-1.4	0.8-1.5
F	≤0.75	≤0.8

5.3.2 Personal Spacing Propensity: Revised Body Ellipse with Buffer

As stated previously, pedestrians tend to keep away from walls, walkway furniture, other pedestrians, and other obstructions. This characteristic requires analysts to discount the unused space for determining actual facility service level. In this section, another way of the body ellipse representation is presented to adjust the space category in the HCM pedestrian LOS criterion for walkway as well. In the HCM, there is a recommendation of determining effective walkway width. The effective walkway width is defined as the portion of walkway that can be used effectively by pedestrians so that they can keep away from walkway obstructions and maintain the minimum distance from other pedestrians, that is, the difference between total walkway width and the minimum distance from obstruction (TRB, 2000). Since it has not been considered in pedestrian walkway LOS in the HCM, the study proposes a method that incorporates this matter while revising pedestrian body ellipse for space requirement and applying it to the lowest level of space LOS grade.

The first step of revising body ellipse is trimming off any distances from obstructions that are less than 0.2 m (0.06 ft) because, based on observations from the empirical study (Strawderman et al., 2010), these distances can be interpreted as the moment each pedestrian entered a room or elevator, sat on a bench, left/entered the region of interest, or walked in a group shoulder to shoulder (unavoidable distance from obstructions) unless they conflicted with other pedestrians. These data were canceled while analyzing personal spacing characteristics in a reliable way since these were neither normal nor homogeneous travelling behavior in terms of general individual's spacing tendency. The next step is determining the descriptive statistics with respect to the percentile minimum distance from obstructions so that the lowest level of individual space (i.e., level E) could be defined by the square of the revised buffer length (two times of lowest percentile AMD) from obstructions. Each interval between two consecutive 16.7th percentiles was equally spaced as proposed in pedestrian LOS literature (Sisiopiku et al., 2007; Muraleetharan et al., 2004; Landis et al., 2000; Khisty, 1994) and this approach is applied to the rest of LOS methods in the study as well. The adjusted intervals of personal spacing in terms of percentile minimum distance from obstructions are shown in Table 5.3:

Table 5.3 Space LOS based on Revised Body Ellipse

Percentile	Percentile AMD (m)	Buffer length 2*AMD (m)	Space (m^2)
≥83.5	≥1.14	≥2.28	≥5.20
66.7-83.5	0.93-1.14	1.86-2.28	3.45-5.20
50.0-66.7	0.85-0.93	1.70-1.86	2.89-3.45
33.4-50.0	0.70-0.85	1.40-1.70	1.96-2.89
16.7-33.4	0.48-0.70	0.96-1.40	0.92-1.96
≤16.7	≤0.48 →	≤0.96 →	≤0.92

Note: Buffer length and revised space are determined using the percentile AMD and buffer length respectively.

The revised body ellipse with buffer in lowest percentile in this study was 0.96 m, and the bottom line of individual space is 0.92 m^2 as delineated in Table 5.3 and Figure 5.1.

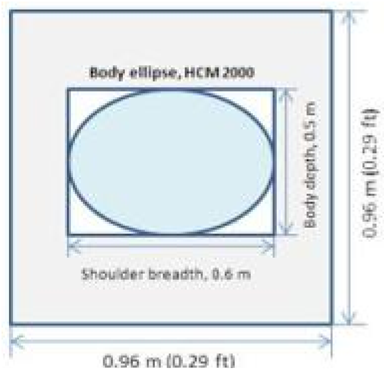

Figure 5.1 Body Ellipse with Buffer

The minimum pedestrian body ellipse area for a standing pedestrian in HCM is 0.3 m^2 (0.5 m * 0.6 m), and the recommended individual area is 0.75 m^2 for facility evaluation and design purposes. This recommended area works as the lowest level LOS in the space category. The reason why they set 0.75 m^2 as the bottom line of LOS was that the pedestrian flow showed its peak in volume at the instant of 0.5 m^2 pedestrian space, and they adjusted the value for design purpose. In a similar fashion, it is suggested to replace the lowest value in HCM LOS with the revised lowest value in space column in Table 5.3 setting it as the lowest level. This substitution yields 1.2 (= 0.92 m^2 / 0.75 m^2) rate of change. The last step is adjusting LOS rating scale for space based on the newly determined pedestrian space while applying a rate of change to each HCM LOS grade. The revised LOS table for pedestrian space is displayed in Table 5.4.

Table 5.4 Revised LOS for Pedestrian Space

LOS in space	Before (in HCM) (m^2/ped)	After (proposed) (m^2/ped)
A	≥5.6	≥ (5.6 * 1.2) = 6.72
B	3.7-5.6	4.44-6.72
C	2.2-3.7	2.64-4.44
D	1.4-2.2	1.68-2.64
E	0.75-1.4	0.92-1.68
F	≤0.75	≤(0.75*1.2) = 0.92

5.3.3 Delay based LOS

Pedestrians usually navigate in walkways that facilitate various amenities (e.g., bench, water fountain, elevator, door, direction indicator, etc.). People are frequently impeded when they encounter other pedestrians who are utilizing these amenities or may even be impeded by the amenity itself. Additionally, pedestrians are often impeded by opposing pedestrians as stated previously. This leads pedestrians to experience delay while heading toward their destinations even though they can walk at their free speeds if they do not experience impedance. Therefore, there is a need to include a delay factor when measuring the service level of pedestrian walkway. Pedestrian delay is defined as the time difference between walking with the average unimpeded speed and average speed (Bloomingburg & Burden, 2006). To calculate the average instantaneous delay, the following equations can be utilized (see chapter 4 for more information about footage processing for data collection and computational procedure for obtaining traffic performance measures.):

$$\text{Travel distance}: d_i(t) = \sum_{t=1}^{T} \sqrt{(x_{i,t} - x_{i,t-1})^2 + (y_{i,t} - y_{i,t-1})^2}, \quad i = \text{pedID} \tag{5.4}$$

$$\text{Average instantaneous speed: } \overline{s}_i(t) = \sum_{t=1}^{T} d_i(t) \cdot (\text{number of frames/sec}) \tag{5.5}$$

$$\text{Individual's instantaneous delay}: D_i(t) = \frac{d_i(t)}{\overline{s}_i(t)} - \frac{d_i(t)}{\overline{s}_{i,\max}(t)} \tag{5.6}$$

$$\text{Average instantaneous delay}: \overline{D}(t) = \frac{\sum_{i=1}^{N(t)} D_i(t)}{N(t)} \tag{5.7}$$

where: $\overline{s}_{i,\max}(t)$ = average unimpede speed,

$N(t)$ = the number of pedestrian up to frame t

Once the average instantaneous delay (AID) is calculated, the loss in distance (LD) due to delay can be calculated as follows:

$$\text{LD} = \overline{s}_{\max}(t)\overline{D}(t) - \overline{s}(t)\overline{D}(t)$$
$$\text{where: } \overline{s}_{\max}(t) = \frac{\sum_{i=1}^{N(t)} \overline{s}_{i,\max}(t)}{N(t)} \text{ and } \overline{s}(t) = \frac{\sum_{i=1}^{N(t)} \overline{s}_i(t)}{N(t)} \tag{5.8}$$

The next step is to divide the length of walkway into six segments so as to assign loss in distance to appropriate unique intervals, which are defined as: level A (<16.7%); level B (16.7%-33.4%); level C (33.4%-50%); level D (50%-66.7%)); level E (66.7%-83.5%); level F (>83.5%). The procedure for the delay-oriented LOS is as follows:

1) Calculate the instantaneous distance for each pedestrian using equation (5.4)
2) Calculate the average instantaneous speed and maximum speed for each pedestrian using equation (5.5)
3) Calculate the instantaneous delay for each pedestrian using equation (5.6)
4) Determine the average instantaneous delay (AID) measure using equation (5.7)
5) Calculate the loss in forward distance (LD) due to AID; domain change from time to space (distance)
6) Split the length of walkway into six evenly that can be appropriately mapped to each grade A to F.
7) Determine on which range the calculated LD falls

5.3.3.1 Operational Example

The same site was considered to compute delay based LOS as discussed in the previous operational example for the revise space LOS. The obtained AID was 7 sec /

ped, average instantaneous unimpeded speed was 2.5 m/s, and average instantaneous speed was 1.3 m/s. The obtained loss in distance is given by: LD = (2.5 – 1.3) m/s * 7 sec / ped = 8.4 meters.

Table 5.5 Delay based LOS

Delay LOS	% LD (100%)	Range of LD (out of 24 m)
A	≤16.7	≤4
B	16.7-33.4	4-8
C	33.4-50.0	8-12
D	50.0-66.7	12-16
E	66.7-83.5	16-20
F	≥83.5	≥20

Note: LOS level was divided into six equal sub-intervals as proposed in pedestrian LOS literature (Sisiopiku et al., 2007; Muraleetharan et al., 2004; Landis et al., 2000; Khisty, 1994).

5.3.4 Ratio of Average Speed to Preferred Walking Speed

Preferred walking speed (PWS) is defined as the optimum speed that minimizes the gross energy cost per distance in the psychology research area (Clark-Carter et al., 1986). PWS can be measured by dividing distance walked by the time required, provided there are no obstructions. In this section, data pertaining to any stationary movement or lingering behavior was excluded since PWS may not exist or be infinitesimal regarding these behaviors in reality. According to observations in the study, movements with speeds of approximately 0.5 m/s or less were regarded as stationary or lingering movements. This can be validated by assuming (based on the observation results in Chapter 4; Daamen & Hoogendoorn, 2006; Teknomo, 2006) that the mean speed is 1.4 m/s with a standard deviation of 0.3 m/s (1.4 m/s – 3*0.3 m/s = 0.5m/s). The left picture in Figure 5.2 illustrates the trimmed speed distribution with a mean of 1.34 m/s and a standard deviation of 0.9 m/s. The next step is to extract unimpeded (preferred) speed from the trimmed distribution. This has been done by removing impeded speed out of the trimmed distribution and generating a new distribution as shown in the right picture in Figure 5.2. The average unimpeded speed is 1.42 m/s with a standard deviation of 0.97 m/s.

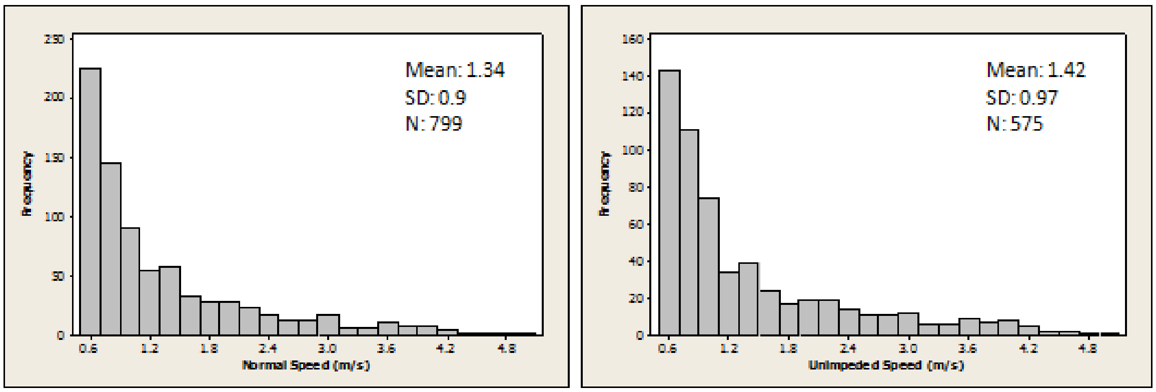

Figure 5.2 Trimmed and Unimpeded Speed Distributions

Table 5.6 shows each percentile speed for normal (trimmed) and unimpeded situations. Since there was difference between them with respect to the number of data and speeds in each range, they have different average speeds as well though they have the same values in each range.

Table 5.6 Percentile Trimmed and Unimpeded Speed

Percentile	Normal speed (m/s)	Unimpeded speed (m/s)
≥83.5	≥2.12	≥2.12
66.7-83.5	1.42-2.12	1.42-2.12
50.0-66.7	1.01-1.42	1.01-1.42
33.4-50.0	0.81-1.01	0.81-1.01
16.7-33.4	0.61-0.81	0.61-0.81
≤16.7	≤0.61	≤0.61

5.3.4.1 Operational Example

As indicated earlier in this section, each speed distribution has been truncated with the lower bound of 0.5 m/s. To construct the rating scale with the lower (0.5 m/s) and upper (1.42 m/s, average unimpeded speed) bounds, the interval between them was uniformly divided into six sub-intervals pertaining to each level of average to PWS ratio as shown in Table 5.7.

Table 5.7 Average PWS Ratio based LOS

LOS	Average to PWS ratio	Speed range (m/s)
A	≥0.88	≥1.26
B	0.77-0.88	1.10-1.26
C	0.67-0.77	0.96-1.10
D	0.56-0.67	0.80-0.96
E	0.45-0.56	0.65-0.80
F	≤0.45	≤0.65

Note: LOS level was divided into six equal sub-intervals as proposed in pedestrian LOS literature (Sisiopiku et al., 2007; Muraleetharan et al., 2004; Landis et al., 2000; Khisty, 1994).

The determined ratio of average to PWS in this study was 0.94 (1.34/1.42) since average speed, including both impeded and unimpeded speeds, was 1.34 m/s, and average unimpeded speed (PWS) was 1.42 m/s. This resulted in service level A while HCM LOS indicates level E with average speed of 0.99 m/s.

5.3.5 Blocking Probability

When analyzing emergent evacuation pedestrian flow or highly congested situation, it is crucial to obtain a specific measure that describes how much pedestrian flow is blocked. This measure can be thought of as a performance of facility, and the blocking phenomenon can also be adequately examined by queueing theory. To obtain a blocking probability for the pedestrian facility, it is necessary to choose an appropriate model beforehand, e.g., M/G/c/c queueing system. In this study, it was assumed that each pedestrian arrival epoch follows Poisson process with an arrival rate of λ, and the service time (S) of each server (i.e., pedestrian area) has a general distribution, G, with an average service time of E[S] = 1/μ. The number of server is c, and they are identical and independent of each other. The facility capacity (i.e., maximum allowable numbers of pedestrian including the ones being served) was also assumed to be finite, c, and the system satisfies steady-state condition (λ < c μ). The service policy of this system is based on first-come-first-served (FCFS). The detailed derivation of system size distribution can be found in Lee and Strawderman (2009).

The system of interest (M/G/c/c) has its structure of exponential interarrival (M), general service time (G), c servers, and finite facility capacity of c. When a new arriving pedestrian (with a rate of λ) sees all c servers are busy (cμ), then the pedestrian's arrival is blocked since the facility has finite capacity as illustrated in Figure 5.3.

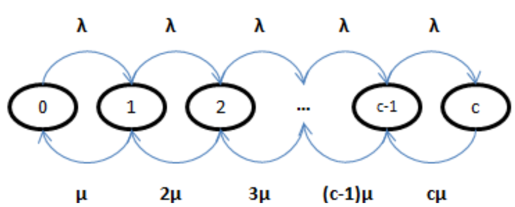

Figure 5.3 State Transition Diagram for M/G/c/c Queueing System

The facility capacity can be calculated by multiplying width (W) and length (L) of facility and dividing them by the area of pedestrian body dimension (A). The detailed pedestrian body dimension (0.5 m * 0.6 m) is discussed in the Highway Capacity Manual (TRB, 2000). So, the facility capacity (c) is calculated using equation (5.9) (Cruz & Smith, 2007; Cheah & Smith, 1994; Tregenza, 1976):

$$c = \left\lfloor \frac{W \cdot L}{A} \right\rfloor \tag{5.9}$$

Then the blocking probability (probability of c pedestrians in the system) of the finite M/G/c/c queue is (Lee & Strawderman, 2009):

$$\begin{aligned} &P_c = \frac{(\lambda/\mu)^c}{c!}\frac{1-\nu}{1-\rho}P_0 \\ &\text{where}: \quad P_0 = \left[\sum_{n=0}^{c}\frac{(\lambda/\mu)^n}{n!}\right]^{-1}, \quad \nu = \frac{\rho R}{1-\rho+\rho R}, \ \rho = \frac{\lambda}{c\mu}, \text{ and} \\ &\lim_{\rho\to 0} R = \frac{1}{4}\left[1+\frac{3E[S^2]}{2E^2[S]}\right]; \ \lim_{\rho\approx 0.5} R = \frac{c}{c+1}; \ \lim_{\rho\to 1} R = \frac{1+Var(S)/E^2[S]}{2} \end{aligned} \tag{5.10}$$

Since a probability is defined between zero and one, the blocking probability-based LOS can be constructed by uniformly dividing a total probability into six sub-intervals (Sisiopiku et al., 2007; Muraleetharan et al., 2004; Landis et al., 2000; Khisty, 1994) correlated with each blocking probability level. For instance, each blocking probability lies: (a) less than 0.17 is level A; (b) 0.17-0.33 is level B; (c) 0.33-0.50 is level C; (d) 0.50-0.67 is level D; (e) 0.67-0.83 is level E; and (f) greater than 0.83 is level F.

5.3.5.1 Operational Example

The dimension of the selected site was 3 m (10 ft) * 22 m (72 ft) with an area of 66 m^2 (720 ft^2). Pedestrian interarrival time followed an exponential distribution with a mean of 14.4627 (sec/ped), and this has been identified by the Kolmogorov-Smirnov test (KS=0.163, p=0.553). The pedestrian arrival rate (λ) was a reciprocal of mean interarrival time, that is, 0.0691 (ped/sec). The service time was log-normally distributed with a minimum value of 1. The mean of the included normal (μ_N) was 1.93, and the standard deviation of the included normal (σ_N) was 1.19 (KS=0.162, p=0.127). The M/G/c/c queueing system was applicable to analyze blocking phenomenon since the interarrival time is exponentially distributed. Based on the parameters obtained previously, the average, variance and second moment of service time were calculated as follows:

$$E[S] = e^{\mu_N + \sigma_N^2/2} = 13.99; Var[S] = e^{2\mu_N + \sigma_N^2}(e^{\sigma_N^2} - 1) = 610.49; \text{ and } E[S^2] = 806.09 \quad (5.11)$$

The service rate (μ), which is reciprocal of mean service time, was 0.072 (ped/sec). Therefore, traffic intensity (ρ) was 0.0044. P_0, R and ν were calculated as shown in equation (5.12).

$$\begin{aligned} &P_0 = \left[\sum_{n=0}^{220} \frac{(0.97)^n}{n!}\right]^{-1} = 0.38;\ R = \frac{1}{4}\left[1 + \frac{3(806.09)^2}{2(13.99)^2}\right] = 1.79;\ \text{and} \\ &\nu = \frac{0.004(1.79)}{1 - 0.004 + 0.004(1.79)} = 0.008 \end{aligned} \quad (5.12)$$

The blocking probability (P_c) can be obtained plugging all necessary values (see equations (5.11) and (5.12)) into equation (5.10), and it was approximately zero (i.e., the chance of pedestrian blocking was scarce) for this pedestrian facility. So, the blocking probability-based LOS was level A.

5.4 Implementation and Results

Based on the proposed LOS methodologies in the previous section, four types of LOS metrics were applied to evaluate the facility performance with the sidewalk data set. The site chosen for implementation was academic sidewalk on the campus of Mississippi State University. The video footage was taken from a camera that is facilitated on top of the building about 10 m (33 ft) above the ground. The dimension of selected site was 3 m (10 ft) * 11 m (36 ft) with an area of 33 m^2 (357 ft^2) as illustrated in Figure 5.4. The footage displayed eight and half minutes of behavior containing 200 pedestrians.

Figure 5.4 Screenshot of the Selected Sidewalk

5.4.1 Space Revision LOS

Two types of adjustment (i.e., reduction in walkway width and revision of personal space) have been proposed in the study. Unlike operational examples in previous section, this walkway had a particular form of setting without wall (limit of sidewalk width). Pedestrians sometimes walked along the extreme edge or over the walkway width when they were even faced with collision to maintain current speed, which means the first method might not be applicable for this sidewalk situation while the second method was still valid to apply. Based on descriptive statistics with respect to percentile minimum distance from obstruction, the obtained lowest level of individual space and rate of change were 1.29 (m^2) and 1.72 (= 1.29 m^2/0.75 m^2) respectively. Following is the revised LOS rating scale for an individual space that the rate of change has been taken into consideration.

Table 5.8 Space Revised LOS

Space revised LOS	Before (in HCM) (m^2/ped)	After (proposed) (m^2/ped)
A	≥5.6	≥ (5.6 * 1.72) =9.63
B	3.7-5.6	6.36-9.63
C	2.2-3.7	3.78-6.36
D	1.4-2.2	2.41-3.78
E	0.75-1.4	1.29-2.41
F	≤0.75	≤1.29

An observed individual space in the study was 5.69 m^2 categorized into an LOS grade C while the other grade based on HCM LOS criteria was A.

5.4.2 Delay based LOS

To implement delay based LOS, it was necessary to obtain the average instantaneous delay (AID), average unimpeded and instantaneous speeds, and loss in distance (LD). As described previously (section 5.3.4), 200 pedestrians were observed within a selected sidewalk that was 11 meter long. The average length of pedestrian trajectory was 11.2 meters since their trajectories were not linear. AID (=3.95 sec/ped) was obtained using equations (5.4) through (5.7), and the determined average instantaneous and unimpeded speeds were 1.36 m/sec and 1.63 m/sec respectively. Then, LD = (1.63-1.36)*3.95 = 1.07 m, which yields 10 % (1.07 m /11 m *100 %) of loss in distance out of the entire length of walkway. Therefore, the delay based LOS of this study turned out to be level A as shown in Table 5.9.

Table 5.9 Delay based LOS Result

Delay LOS	% LD (100%)	Range of LD (out of 11 m)
A	≤16.7	≤1.84
B	16.7-33.4	1.84-3.67
C	33.4-50.0	3.67-5.50
D	50.0-66.7	5.50-7.34
E	66.7-83.5	7.34-9.19
F	≥83.5	≥9.19

5.4.3 Preferred Walking Speed (PWS) based LOS

Sidewalk speed data was split into two parts to apply preferred walking speed based LOS as described in the following table. For the sidewalk application, there was no need to truncate speed distribution because it did not contain any stationary or meandering movement in the footage. The observed average instantaneous and unimpeded speeds were 1.34 m/s and 1.62 m/s that determined ratio of average to PWS in sidewalk study as 0.82 (1.34/1.62).

Table 5.10 Percentile Normal and Unimpeded Speed

Percentile	Normal speed (m/s)	Unimpeded speed (m/s)
≥83.5	≥ 1.80	≥ 1.99
66.7-83.5	1.49-1.80	1.71-1.99
50.0-66.7	1.31-1.49	1.50-1.71
33.4-50.0	1.15-1.31	1.31-1.50
16.7-33.4	0.86-1.15	1.15-1.31
≤16.7	≤ 0.86	≤1.15

To construct the rating scale with upper bound (1.62 m/s, average unimpeded speed), speed was uniformly divided into six sub-intervals as described in the previous section, and the PWS based LOS table was generated in Table 5.11 resulting in level B of PWS based LOS.

Table 5.11 Average to PWS Ratio based LOS

PWS-based LOS	Average to PWS ratio	Speed range (m/s)
A	≥0.84	≥1.35
B	0.67-0.84	1.08-1.35
C	0.50-0.67	0.81-1.08
D	0.33-0.50	0.54-0.81
E	0.17-0.33	0.27-0.54
F	≤0.17	≤0.27

5.4.4 Blocking Probability

The first step that needs to be taken was to record each pedestrian's arrival time and time in system (i.e., travel time) in order to obtain the information about the interarrival time distribution and service time distribution. Goodness-of-fit test showed the interarrival time was exponentially distributed with a mean of 2.56 (sec/ped) (KS=0.095, p=0.068), which means there is no significant difference between distribution of raw data and fitted distribution, and the arrival rate (λ) was 0.39 (i.e., 1/2.56 ped/sec). The same test was also conducted to identify the type of service time distribution. Service time (S) followed a normal distribution with a mean of 8.3 and a standard deviation of 1.12 (KS=0.074, p=0.15). The service rate (μ) was 0.12 (1/8.3 ped/sec). Following key measures can be obtained using expressions previously described in this section:

$$\begin{cases} \lambda = 0.39 \\ E[S] = {}^{1}\!/_{\mu} = 8.3 \\ Var[S] = E[S^2] - E^2[S] = (1.12)^2 = 1.25 \\ E[S^2] = 70.14 \\ c = \left\lfloor \dfrac{W \cdot L}{0.3} \right\rfloor = \left\lfloor \dfrac{3(10)}{0.3} \right\rfloor = 110 \\ \rho = \dfrac{\lambda}{c\mu} = 0.029 \end{cases} \tag{5.13}$$

Parameters listed in equation (5.14) were used to calculate the blocking probability (P_c):

$$\begin{cases} P_0 = \left[\sum_{n=0}^{110} \frac{(3.24)^2}{n!} \right]^{-1} = 0.04 \\ R = \frac{1}{4}\left[1 + \frac{3(70.14)}{2(8.3)^2} \right] = 0.63 \\ \nu = \frac{0.029(0.63)}{1 - 0.029 + 0.029(0.63)} = 0.019 \end{cases} \tag{5.14}$$

Then, the blocking probability (P_c) for pedestrian walkway in this study was calculated putting equations (5.13) and (5.14) into equation(5.10), and it was approximately zero, which means pedestrian blocking was unlikely to happen indicating a level A LOS.

5.5 Discussion and Conclusion

Pedestrian LOS defined in HCM can be thought of as a microscopic view of analysis while this study is based on macroscopic way. Both approaches have inherited advantage and disadvantage altogether. HCM methodology is easy to apply, and it is good for initial pedestrian facility service level assessment since all ingredients needed to analyze are overall average speed and the number of pedestrian in the region of interest given a certain amount of time (usually 15 minutes). However, as pedestrian traffic becomes complicated, it is not enough to analyze its level of service only with space, speed and flow rate metrics because they do not explain the impact of numerous interactions due to various environment. This study is an extension of existing HCM LOS that provides a revision of space as well as another use of speed metric based upon microscopic view of analysis to incorporate instantaneous interaction with environment.

This method is useful to obtain the detailed aspects after conducting initial rough analysis based on the HCM methodology.

The first aspect considered was individual space. HCM LOS has a standard type of body ellipse (0.5 m *0.6 m) with extended ellipse (0.75 m^2) for general design purpose. The determined pedestrian space was 5.69 (m^2/ped) that belongs to level A when HCM space rating scale was applied while this study showed level C. The reason that those methods indicate dissimilar results was that there was a difference in defining body ellipse. HCM uses the same body ellipse for every situation, but this study applied situation specific ellipse based on individual average minimum distance from environment (obstacles, other pedestrians, amenities, etc.) with buffer. One of the drawbacks of HCM methodology is it lacks individual spacing propensity that can be improved by using buffer area. Buffer is generally used to describe the minimum distance from obstruction along the entire pedestrian trajectory within each frame. Encompassing a buffer area with body ellipse is crucial because walking speed and density can be impacted as it changes. Pedestrians who have greater body ellipse than HCM's can be regarded as they endeavor to keep their distance from obstruction while changing their direction or even speed, which affects pedestrian density within region of interest. The utility of this approach can be better understood when aligning delay-based LOS discussed below.

The delay-based LOS was useful for evaluating service level of a walkway that facilitates relatively many resource points for pedestrians. Delay may occur when people decelerate or stop to acquire something they need if the facility contains resource points. This is a natural and direct cause of delay, and it can be investigated simply observing walking speed and acceleration. Another phenomenon to consider is indirect delay. It has been frequently observed in this study that pedestrians keep their preferred speed (average or higher) though pedestrian density increases, which means they actively change their trajectories (non-linear fashion) to maintain preferred distance (minimum distance as described earlier) from obstruction keeping current speed. In this situation, they appear longer in the footage than others who take linear trajectory while changing speed (mostly decelerating). It can be regarded that they walk relatively longer distance to complete their navigational tasks since they change trajectory frequently to avoid collision while maintaining current speed. This phenomenon causes increase in travel distance, which results in delay and loss in distance. The obtained delay-based LOS is level C, and it shows the same result as space revised LOS.

As a subsidiary analysis of speed characteristic, PWS-based LOS has been developed. The calculated HCM LOS in speed is level A while PWS-based LOS is level B indicating that pedestrians experienced delay probably due to spacing propensity and loss in distance. The difference between HCM LOS grade and PWS-based LOS grade shows analyzing facility service level with only an overall speed metric is not enough. The advantage of using PWS is that PWS can be applied to measure walking efficiency because LOS in speed is indirectly impacted by pedestrians' navigational performance. PWS is versatile to incorporate continuously changing environment (instantaneous and unimpeded speeds) into PWS ratio. An additional aspect to notice is there might be a situation that average speed is greater than PWS obtained if a number of pedestrians are in hurry and walk hastily utilizing restricted space efficiently though they are faced with obstructions. The study does not comprise this situation for a certain reason. It usually happens when there are a couple of dissimilar trip purposes in the sidewalk that is composed of distinctive pedestrians, e.g., commuters and tourists.

Analytic queueing systems constitute a flexible tool for investigating pedestrian traffic flow. Queueing models are simple to manipulate and give credible performance measures such as average waiting time, throughput, blocking probability, etc. Understanding blocking mechanism is crucial when analyzing facility performance under congested or emergent situation, since pedestrian facilities are usually limited in capacity. This article examined blocking phenomenon, which has not been discussed in literatures or the Highway Capacity Manual (TRB, 2000) in authors' knowledge. Queueing theory may provide a fundamental foundation of microscopic-to-macroscopic analysis. Even though two case studies in this paper showed approximately zero blocking probabilities (level A), there existed nonzero blocking probabilities in specific area for certain periods of time. This may require decomposing system into a set of finite queues, and reconstructing system to a network structure with microscopic traffic factors so as to obtain a steady state probability through more realistic simulation if necessary.

There are some potential future works pertaining to improving the performance of LOS measurement. As a simple application of LOS, this study presented various methodologies for walkway service level. It is necessary to develop pertinent service level assessment tools that can be applicable to sidewalks and transportation facilities comprising diverse forms of trip purposes. It is expected to apply different metrics at a time when assessing service level of a multimodal transportation facility, since it usually shows dissimilar facets of traffic characteristics depending on locations in the facility

One of the most effective ways to analyze group dynamics is to study the inter-relationship between pedestrian flows. Since HCM methodology does not include the effect of a predominant flow against a reverse non-dominant, it is worth investigating it determining frictional force based LOS rating scale not to speak of encompassing microscopic view of data.

Ramifications of bodily dimension would be another future work. HCM proposed average overall body ellipse with an area of 0.3 m^2 for individual and extended one of 0.75 m2 for design evaluation. It seems to be over-generalized. There is a need to provide a classification of bodily dimension in regard to age and gender based on bodily dimension statistical encyclopedia. Finally, an equation that incorporates the HCM LOS and the proposed LOS methodologies in the study will be developed to predict pedestrian walkability (section 4.5) as a measure of pedestrians' perceived LOS.

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APPENDIX A

INSTITUTIONAL REVIEW BOARD APPROVAL LETTERS

A.1 IRB Approval Letter for Chapter 2

MISSISSIPPI STATE UNIVERSITY

Compliance Division
Administrative Offices
Animal Care and Use (IACUC)
Human Research Protection Program (IRB)
1207 Hwy 182 West
Starkville, MS 39759
(662) 325-3496 - fax

Safety Division
Biosafety (IBC)
Radiation Safety
Hazardous Waste
Chemical & Lab Safety
Fire & Life Safety
70 Morgan Avenue
Mississippi State, MS 39762
(662) 325-8776 - fax

http://www.orc.msstate.edu
compliance@research.msstate.edu
(662) 325-3294

March 19, 2010

Hohyun Lee
ISE
Mailstop 9542

RE: IRB Study #10-030: Cognitive Information Process, Mental Workload, and Performance in Pedestrian Navigation

Dear Mr. Lee:

The above referenced project was reviewed and approved via expedited review for a period of 3/19/2010 through 3/15/2011 in accordance with 45 CFR 46.110 #4. Please note the expiration date for approval of this project is 3/15/2011. If additional time is needed to complete the project, you will need to submit a Continuing Review Request form 30 days prior to the date of expiration. Any modifications made to this project must be submitted for approval prior to implementation. Forms for both Continuing Review and Modifications are located on our website at http://www.orc.msstate.edu.

Any failure to adhere to the approved protocol could result in suspension or termination of your project. Please note that the IRB reserves the right, at anytime, to observe you and any associated researchers as they conduct the project and audit research records associated with this project.

You must use copies of the stamped consent form for obtaining consent from participants.

Please refer to your docket number (#10-030) when contacting our office regarding this project.

We wish you the very best of luck in your research and look forward to working with you again. If you have questions or concerns, please contact Jonathan Miller at jmiller@research.msstate.edu or call 662-325-2238.

Sincerely,

Jonathan Miller, CIP
IRB Officer and Assistant Director

cc: Lesley Strawderman (Advisor)

Office of Regulatory Compliance • Post Office Box 6223 • Mississippi State, MS 39762

A.2 IRB Approval Letter for Chapter 4

MISSISSIPPI STATE
UNIVERSITY

Compliance Division
Administrative Offices
Animal Care and Use (IACUC)
Human Research Protection
Program (IRB)
1207 Hwy 182 West, Suite C
Starkville, MS 39759
(662) 325-3496 - fax

Safety Division
Biosafety (IBC)
Radiation Safety
Hazardous Waste
Chemical & Lab Safety
Fire & Life Safety
70 Morgan Avenue
Mississippi State, MS 39762
(662) 325-8776 - fax

http://www.orc.msstate.edu
compliance@research.msstate.edu
(662) 325-3294

August 25, 2010

Hohyun Lee
ISE
Mailstop 9542

RE: IRB Study #09-206: Analyzing Pedestrian Traffic Behavior: A Field Study for the Validation of Pedestrian Simulator

Dear Mr. Lee:

Your request for continuing review of the study listed above was reviewed and approved via expedited review in accordance with 45 CFR 46.110 #7 on 8/25/2010.

You are granted permission to continue your study as approved effective immediately. The study is next subject to continuing review on or before 9/15/2011, unless closed before that date.

If additional time is needed to complete the project, you will need to submit a Continuing Review Request form 30 days prior to the date of expiration. Any modifications made to this project must be submitted for approval prior to implementation. Forms for both Continuing Review and Modifications are located on our website at http://www.orc.msstate.edu.

Please note that the MSU IRB is in the process of seeking accreditation for our human subjects protection program. As a result of these efforts, you will likely notice many changes in the IRB's policies and procedures in the coming months. These changes will be posted online at http://www.orc.msstate.edu/human/aahrpp.php.

Please refer to your IRB study number (#09-206) when contacting our office regarding this project.

We wish you the very best of luck in your research and look forward to working with you again. Contact Christine Williams (cwilliams@research.msstate.edu or call 662-325-5220) if you have any questions or require further information.

Sincerely,

Christine Williams
IRB Compliance Administrator

cc:Lesley Strawderman

Office of Regulatory Compliance & Safety • Post Office Box 6223 • Mississippi State, MS 39762