SEMIAUTOMATED ANALYSIS OF PEDESTRIAN BEHAVIOUR AND MOTION FOR MICROSIMULATION OF TRANSPORTATION TERMINALS

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ABSTRACT

Pedestrian Microsimulation is used to design and evaluate the circulation of pedestrians in buildings and pedestrian spaces during the design phase so that changes and optimizations can be made. However, models need input data such as walking speeds which reflect the population modelled. Mass amounts of detailed data collection is therefore needed, but current methodologies are either too slow or use expensive equipment and do not consider finer details. A new methodology called Semiautomated Tracking is created for tracking pedestrians from video footage and generating walking speeds based on manually assigned tags. The methodology is verified against manually calculated movement speeds and applied to a multi-factor analysis of a transportation terminal, revealing that Semiautomated Tracking can quickly generate detailed data for more people and with similar results. Differences were also found between the Canadian data and international guidance, highlighting the importance of the methodology and encouraging future efforts for development.

ACKNOWLEDGEMENTS

This project would not have been possible without the help and support of numerous people and organizations, towards whom I would like to express my sincerest gratitude. Thank you to Arup’s teams in Canada and the UK for conversations providing their knowledge, support, and access to MassMotion which inspired this project. Thank you to VIA Rail Canada and the station staff for their permission and assistance in designing and performing the data collection in the initial study, and Kaleigh from Carleton University for their assistance in data collection at the terminal. Thank you to the stadium and event management for their support and permission for the stadium study.

Thank you to Joan Charmant, creator and developer of Kinovea, a software critical to my project and thesis.

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Thank you to the Society of Fire Protection Engineering foundation for funding additional equipment for future studies, and to the Government of Ontario for their financial support.

Most importantly, thank you to my Supervisor Dr. John Gales, who provided me with the tools, advice, and experiences which continue to drive me and my research forward to new discoveries in pedestrian modelling and transportation engineering.

Lastly, thank you to my family and my girlfriend Kate for supporting me throughout the challenges of this endeavour.

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DECLARATION OF CO-AUTHORSHIP & SCHOLARLY OUTPUTS

The contents of this thesis and the work described has been completed by Timothy Young under Dr. John Gales' supervision. Some chapters of this thesis contain content that has been modified from existing publications that were written by the author but influenced by several other colleagues on the research team.

The work described in Chapter 4, Section 4.1 is based on research completed at York University. The research was published in the Journal of Building Engineering in April 2021. The work is included in Appendix A and is cited as T. Young, J. Gales, M. Kinsey and W. C.-K. Wong, "Variability in stadia evacuation under normal, high-motivation, and emergency egress," *Journal of Building Engineering,* vol. 40, no. 1, p. 102361, 2021.

The author, Timothy Young has also written or co-authored additional publications during the course of his thesis. While not directly related to the thesis, the work performed on these publications influenced the overall direction of the thesis project. These publications are included in thesis appendices E, F and G and are cited as follows:

L. Folk, K. Gonzales, J. Gales, M. Kinsey, E. Carattin and T. Young, "Emergency Egress for the elderly in care home fire situations," *Fire and Materials,* vol. 44, no. 4, 2020.

J. Ferri, T. Young and J. Gales, "Authenticating Crowd Models for Stadium Design," in *Fire and Evacuation Modelling Technical Conference 2020*, Virtual, 2020.

R. Champagne, T. Young, J. Gales, M. Kinsey and B. Weckman, "Fire Evacuation and Strategies for Cultural Centres," in *Interflam 2019: 15th International Conference and Exhibition on Fire Science and Engineering*, Windsor, UK, 2019.

Chapter 1: Introduction

1.1 Transportation Terminal Circulation

Transportation terminals play an important role in a country's infrastructure, facilitating the movement of people to board vehicles and travel across transportation networks. These facilities may include airports, bus hubs, railway stations, and ferry terminals. Ensuring the safe and efficient flow of passengers through these environments is of utmost importance, especially as these facilities may be required to serve thousands of people every day. The efficient, uncrowded flow of passengers contributes to a pleasant experience which may be helpful in encouraging passengers to continue to use the facility and infrastructure. Conversely, poor passenger flow and crowding may encourage passengers to seek other travel methods instead [1]. In extreme cases, crowding can lead to crowd crush or overcrowding conditions, resulting in injuries or death [1] [2]. Thus, engineers must design these spaces to ensure good, safe pedestrian flow which accounts for the behaviours of the occupants.

Pedestrian circulation engineering revolves around a concept called Level of Service (LOS). LOS evaluates traffic flow and was primarily developed for highways for measuring and categorizing attributes such as travel speed and traffic signal delay on a scale from A (Freeflow conditions) to F (Highly congested, Complete breakdown in flow). In the pedestrian context, LOS is evaluated by measuring pedestrian density in persons per square meter, space per pedestrian, or pedestrian flow rate in pedestrians per minute per meter of width [3]. The different levels of service are illustrated in Figure 1.1 below. This has impacts on pedestrian walking speed, comfort, and safety. At low levels of service and high density, crowd crush and other safety concerns begin to mount.

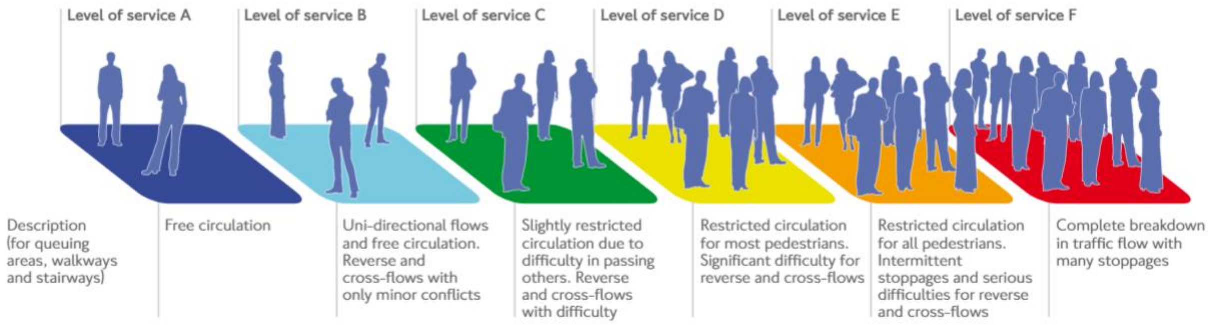

Figure 1.1: Fruin levels of service [4]

Different LOS measures, values, and acceptable limits may exist for different areas or pieces of infrastructure, such as platforms, waiting areas, queues, stairs, and concourses [3]. It is the engineer's responsibility to ensure that the designed spaces meet or exceed the minimum level of service in various scenarios as set by the client. These scenarios are meant to simulate the operations of the terminal in rush hour conditions, but may also include additional situations such as off peak, events or emergencies [5] [6] [1].

1.2 Pedestrian Microsimulation and Modelling Tools

One tool involved in the design of these spaces is Pedestrian Modelling Software. This allows designers and engineers to create 3D models of prospective facility designs, populate it with virtual 'agents' representing people, and then simulate their actions and movements. The results from the model allow engineers to spot potential problems in pedestrian flow such as congestion or crowding and make changes in the design stage to address these issues and assure compliance with building codes and regulations. The modelling software can also be used to estimate travel times within certain areas, or even determine where people are likely to look for wayfinding sign placement [7]. This software has been used in the creation and renovation of complex buildings and infrastructure, including Toronto's Union Station [1]. While not the initial focus of this project, the software is also used in fire and life safety design, ensuring that building occupants can egress safely in the event of a fire or other emergency [2].

Pedestrian modelling software is able to easily evaluate the level of service for entire structures while factoring in the differences in LOS calculations, allowing engineers to quickly pinpoint areas which do not meet client specifications. This can be visualized in a variety of ways, including graphs and heatmaps. Figure 1.2 below demonstrates an instantaneous LOS heatmap of an egressing crowd of pedestrians.

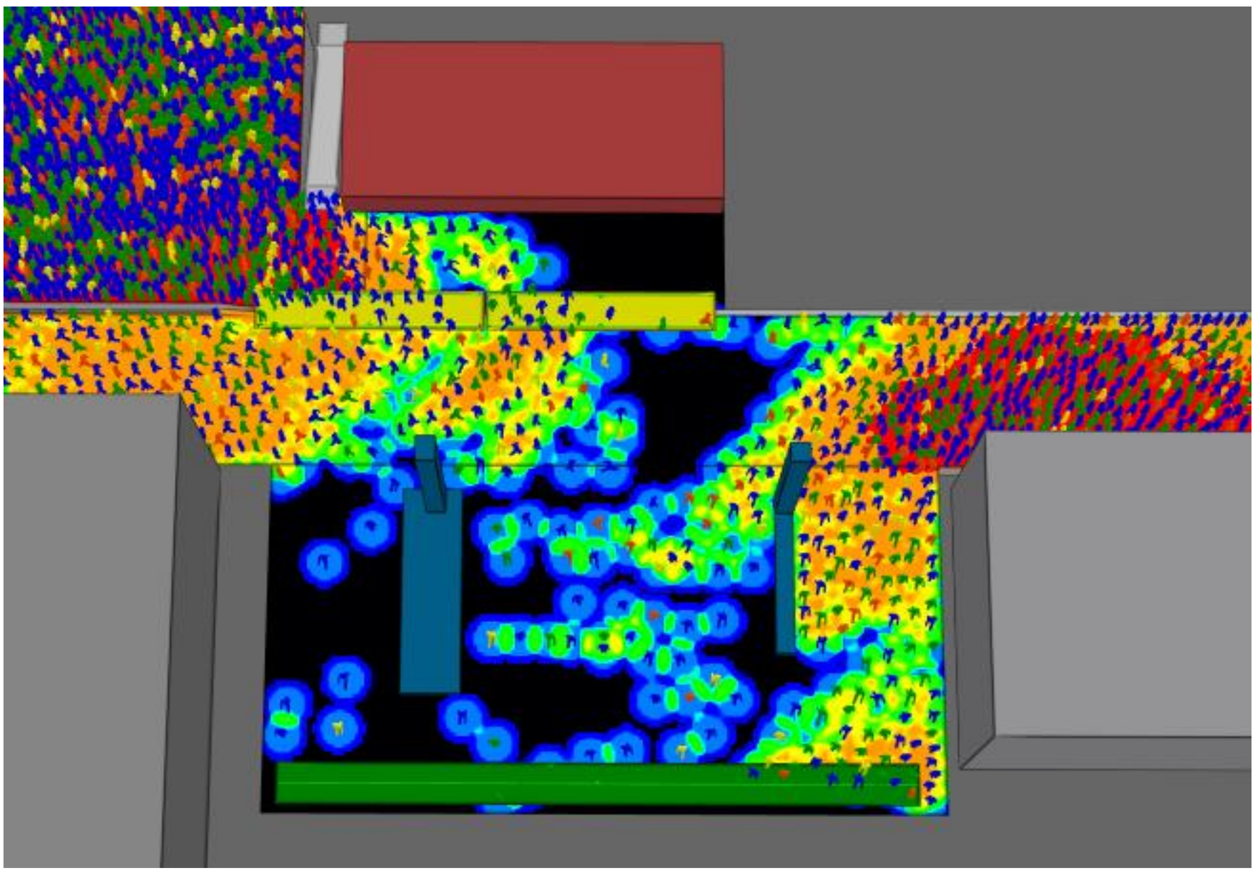

Figure 1.2: Instantaneous Fruin LOS Heatmap in Pedestrian Modelling Software

Pedestrian Modelling software can provide powerful insights which influence building and transportation terminal design. However, this software relies heavily on pedestrian motion models and input data to best estimate potential results. Moreover, the field of pedestrian modelling is still evolving and developing, thus current software may not include parameters or effects to accommodate new or undiscovered human factors and resulting behaviours.

1.3 Human Factors in Pedestrian Modelling

Transportation terminals should be designed as inclusive spaces that accommodate people of all abilities. As such, pedestrian modelling software does not necessarily assign a single value to agent attributes such as movement speed.

One of the inputs for the model is a walking speed distribution which is meant to represent the population being modelled. Currently, modelling software includes default profiles which are based on past studies. However, walking speeds vary significantly due to a number of factors, including different locales and facility types [3]. Thus, these included profiles may not be fully representative of the populations and behaviors being modelled. One researcher noted that there is a significant lack of Canadian input data available while attempting to model Canadian subway stations [4].

The thought process and actions of people may also vary between people. Pedestrian simulation software attempts to accommodate this by modelling the tasks conducted by people as they move through the environment. This could include the completion of different tasks in the terminal by visiting and dwelling in different locations, route selection to go from one place to the other, where to wait, where to queue, and so on [7] [5]. This can be influenced by many factors, including mobility impairments or luggage. However, behaviour is highly difficult to model as it tends to be highly variable depending on the situation and environment. Pedestrian models make assumptions about behaviour which may differ from real-world results, and a much stronger research base is needed to improve the reliability of pedestrian models [8].

Mass amounts of locally collected data is therefore needed to reduce uncertainty and improve accuracy of pedestrian models. However, this analysis generally requires a significant amount of time-consuming human input. Computer Vision technology makes it possible to automate this process [5] [6]. However, the benefits of this technology have not been directly linked with microsimulation applications, and the fully autonomous methods do not allow for more detailed demographic or context analysis.

1.4 Research Motivation

This work is motivated by the need for more detailed input data and validation for pedestrian microsimulation software. More detailed data will permit models to become more accurate, giving engineers better insights into how occupants may behave, particularly those with disabilities or other impairments. This is of critical importance to designing effective and accessible transportation terminals which incorporate universal design standards. Moreover, an abundance of input and validation data can provide practitioners and researchers with more accurate baselines of how pedestrians move and behave in a variety of different situations and environments. This can be used to support new pedestrian modelling algorithms to further develop and improve upon the software to output more realistic and accurate models for future designs.

1.4.1 Pedestrian Modelling for Transportation Terminal Circulation

Pedestrian modelling of transportation terminals is highly important and is considered during the design stages of a transportation project. However, the current state of the art is far from perfect, and still leaves a high degree of uncertainty. As an example of this, the City of Ottawa's Confederation Line Light Rail Project agreement called for the use of pedestrian modelling to develop and verify the station circulation designs including interior, vertical, and site circulation, as well as the operation of the bus platforms attached to the station. The design was also to be adjusted based on simulation results to ensure that all circulation standards were met, including the levels of service set out by the City of Ottawa [9]. Table 1.1 below illustrates the acceptable Levels of Service which should have been reflected and achieved in the pedestrian model.

Table 1.1: Ottawa Light Rail Transit Minimum Level of Service Specifications [9]

The following levels of service indicated below shall be provided in the Design of public spaces as referenced in other parts of this article:

Location	Level of Service (LOS)	Measure
Platforms (Normal)*	C	$0.8m^2$ per person
Platforms (Emergency)*	D	$0.4m^2$ per person
Waiting Areas	C	$0.8m^2$ per person
Passageways – 1 way	D	50 ppm per metre
Passageways – 2 way	C	40 ppm per metre
Stairways – 1 way	E	55 ppm per metre
Stairways – 2 way	D	35 ppm per metre

**Note: Normal Platform refers to the level of service during the daily peak 15 minutes. Emergency Platform refers to the level of service provided during an Emergency in which an incoming fully loaded Train must evacuate onto a Platform with waiting Passengers at the daily peak 15 minutes.*

Following the opening of the Confederation Line in October 2019, overcrowding at terminal stations, particularly in the bus transfer loops became apparent. In response, bus routes were rearranged to spread out waiting passengers, bus services were increased, and in some cases bus platforms were widened. Further changes to one station would include the installation of an additional elevator [10]. While this helped resolve some crowding issues, the need for such quick retrofits demonstrates that pedestrian modelling can still improve. If models had shown that crowding on the bus loop were to be an issue, the changes could have been incorporated into the original construction, reducing, or eliminating the problems later on. However, without more accurate data, there is no guide as to what these improvements need to reflect.

1.4.2 Pedestrian Modelling for Human Safety in Transportation Terminals

When overcrowding conditions exist, safety concerns begin to mount. In terminal concourses, pedestrian crush conditions begin to be a concern. They may also be indicative of other fire safety problems. In 2018, construction and post-traffic concert crowds coincided at Union Station in Toronto. With only 2 out of the 5 available entrance doors available, a large crowd quickly filled the walkway as people attempted to squeeze through the bottlenecked entrance. The incident was circulated on social media and both the City of Toronto and the construction company were fined a combined total of over $55,000 for failing to maintain a means of egress free of obstruction [11].

Platforms also pose significant risks to passengers when overcrowding conditions exist. In 2015, a commuter sustained fatal injuries after his backpack got caught on a departing train. The incident occurred during the height of rush hour, while the commuter was walking on a narrow, crowded section of the platform [2].

While these scenarios demonstrate extreme conditions, they highlight the importance of considering crowd flow, behaviour, and congestion to ensure that these situations do not occur. Furthermore, the ability to analyze passenger behaviours on platforms and/or in stations in these situations could give better insight into how people may act so that situations can be more easily managed if not altogether prevented.

1.4.3 Limited Existing Data and Case Studies

The analysis methodology for pedestrian motion can be divided into two types – Manual tracking and Automated Tracking. Each type of tracking had its benefits and drawbacks.

Manual pedestrian tracking involves timing pedestrians as they walk between two predetermined points through a corridor. This can be done either with pre-recorded videos analyzed after recording or with in-person notetakers situated on-site. The additional flexibility of having live notetakers to do timing means that it is still possible to collect data in places where third-party video recording is prohibited or where ethics are a concern [12]. Notetakers can also provide more detailed information on the people being tracked in low-density environments. Alternatively, security camera footage may be used if provided by the site being analyzed, thus minimizing, or eliminating the setup of additional equipment. However, manual tracking is time consuming for generating pedestrian walking speeds, especially in larger and denser environments [13]. More importantly, it can be less accurate in spaces where pedestrians pause, speed up, slow down, or walk at an angle. Instead, a method is needed for continuous tracking so that partial paths and nonlinear trajectories can still be measured.

Automated pedestrian tracking is a higher-tech solution. Video cameras set up orthogonally to the floor and providing a top-down view can be used to generate footage which is then analyzed using automated computer software [14]. This software uses computer vision techniques to automatically identify and track pedestrian as they walk through the environment. Alternate technologies such as LIDAR may also be used [15]. This method can effectively resolve the above issues of partial paths and nonlinear trajectories but introduces a new challenge; Whereas manual tracking easily allows for a degree of differentiation between different types of pedestrians and behaviours, automated systems consider movement speeds of the entire population. Thus, for the most accurate picture of how different pedestrians move and use pedestrian spaces, a new methodology is needed that allows for both the accuracy of computer vision tracking and the differentiation provided by manual pedestrian analysis.

1.5 Research Focus and Scope

This project aims to develop a methodology to determine the impact of human factors and accessibility aspects on behaviours and movement speeds within transportation facilities. Software plugins will be developed to interface with object tracking software to generate movement speed profiles based on manually assigned context tags. Factors such as stress state, and persons with visibly restricted mobility will be examined and used to apply these tags. Additional behaviours, such as waiting locations, will also be analyzed. Finally, technology from alternative methods of data collection will be examined to determine their potential effectiveness for evaluating future projects.

1.6 Research Objectives

Considering the need for more detailed pedestrian analysis for microsimulation, the overarching research question is to determine if it is possible and beneficial to combine automated tracking software with detailed demographics information.

The objectives of this research is as follows:

1. Create software to generate pedestrian movement speed profiles based on input data, including differentiation between different types of pedestrian
2. Review and evaluate datasets of pedestrian motion in public spaces
3. Identify different common behaviours based on external environmental stimuli and human factors
4. Evaluate the influence of human factors on movement speeds
5. Evaluate the benefits, limitations, and potential use of the developed technology for future studies and improvement

1.7 Thesis Outline

This chapter is an introduction to the overall topic, focus, and objectives of this project.

Chapter 2 is a literature review, summarizing relevant background information and research that has been previously performed. The chapter provides the background on pedestrian modelling, historic movement profile generation, modern developments in technology, and modern station design guidelines. An example of Pedestrian Microsimulation Software, MassMotion is described and outlined, as well as its applications in transportation terminal circulation. With this, gaps in current practice and research needs are outlined.

Chapter 3 describes the creation of a new methodology for collection of pedestrian trajectories and generation of movement profiles. The new methodology makes use of Open-Source tracking software and a new post-processing program to generate walking speeds of people from video footage. A verification test of the methodology is carried out against manual tracking, using footage from a passenger rail station.

Chapter 4 applies the methodology to the analysis of a transportation terminal. A previous study observed circulation of pedestrians in stadia as they egressed the stands under various stimuli. Behavioural aspects based on stimuli are highlighted to demonstrate the effects on pedestrian behaviour, including resulting pedestrian flows in high-stress situations.

In the transportation terminal study, similar aspects to the stadium study are highlighted and analyzed using the software to generate pedestrian movement profiles. The data for this study comes from the author's previous study on group behaviour within transportation terminals. Focus is given to high-stress situations, luggage, and accessibility aspects. Following the study, the benefits, limitations, and potential uses of the new methodology are compared to other existing methods currently available or under development.

Chapter 5, the final chapter, provides conclusions on the project's results and explains how the results and methodology can be used by researchers or practitioners for future analysis of transportation terminals. Furthermore, the chapter outlines how the use of this methodology can improve user confidence in pedestrian microsimulation model development through the use of more refined input and validation data.

The appendices include additional information which could not be fully included within the narrative of this thesis. Appendix A contains the fulltext of *Variability in Stadia Evacuation under Normal, High-Motivation, and Emergency Egress*, of which an excerpt was used for Chapter 4. Appendix B contains the VBA code for Profile Generator, which was used to calculate movement speeds and generate profiles as part of the Semiautomated Tracking methodology. Appendix C contains the raw movement speeds for each profile, as well as sample calculations used to generate the speed for one track. Finally, Appendix D contains the Minitab Statistic Analysis reports for Chapter 4.

The appendices also contain additional contributions to my degree outside of the narrative of this thesis, including publications which I co-authored. These projects gave additional insights which helped guide the thesis. Appendices E, F and G contains the publications *Emergency egress for the elderly in care home fire situations, Authenticating Crowd Models for Stadium Design, and Fire evacuation and exit design strategies for cultural centres*, respectively. They represent a progression from hand records (Appendix E) to manually tracked movement speeds (Appendix F) and finally potential applications of the Semiautomated Tracking Methodology.

Chapter 2: Background and Literature Review

This section provides the reader with a selection of published literature to establish the background of pedestrian modelling software, the verification and validation of said software including knowledge gaps, current methodologies in use or development, and the guidelines and considerations that are recommended for the design of modern transit terminals.

2.1 History of Pedestrian Movement & Modelling

The field of examining pedestrian flow in transportation terminals is well established, with London Transport attempting to study the flow of passengers in subway station corridors to inform the design of future stations in 1958. It was found that flow rates are directly proportional to width, movement on stairs is slower, and pedestrians slow in crowded conditions. The methodology at the time for measuring speeds included a researcher walking with the flow of the crowd between two points and timing the journey [16].

The effect of crowds moving slower in dense conditions was expanded upon by John Fruin, who produced the Level of Service concept for pedestrians. This confirmed London Transport's observations and provided further quantification of pedestrian walking speeds at differing crowding levels [3]. Fruin also established different types of behaviour in queues based on different uses of space in transportation terminals. Platform queues to enter a train were different from queues to purchase tickets, or board an escalator. Ramps, stairs, and escalators also demonstrated different needs and walking speeds. As such, different Level of Service criteria were established for walkways, queuing areas, and vertical circulation [3].

Early attempts at simulating pedestrian flow included fluid dynamics models. At the time, these models were designed to apply fluids theories to pedestrian motion. One study noted that validation required further and more sophisticated comparisons between the model and real-life observed data [17]. Helbing's fluid dynamics model examined pedestrians as fluid particles on a more detailed level, simulating flow lanes and moved toward modelling each particle individually. At the time, Helbing noted that the model could be potentially formulated for computer simulations, of which could be directly compared to films of pedestrian crowds [18].

That future work manifested in the form of the Helbing-Molnar Social Force Model. The Social Force Model introduced a new method of modelling pedestrian motion, based on Newtonian physics [19]. The social forces model is agent-based, where each person and their movements is represented individually on an x-y plane. The social forces model envisions multiple environmental factors which each generate an attracting force or repulsion force. These forces include goal forces to attract an agent towards their next destination, and repulsion forces generated by the built space such as walls or corners to avoid. Another repulsion force is generated by each nearby agent if the crowd is too dense, thus allowing the agents to spread themselves out to maintain personal space while navigating the environment. A visualization of forces acting on an agent is shown in Figure 2.1.

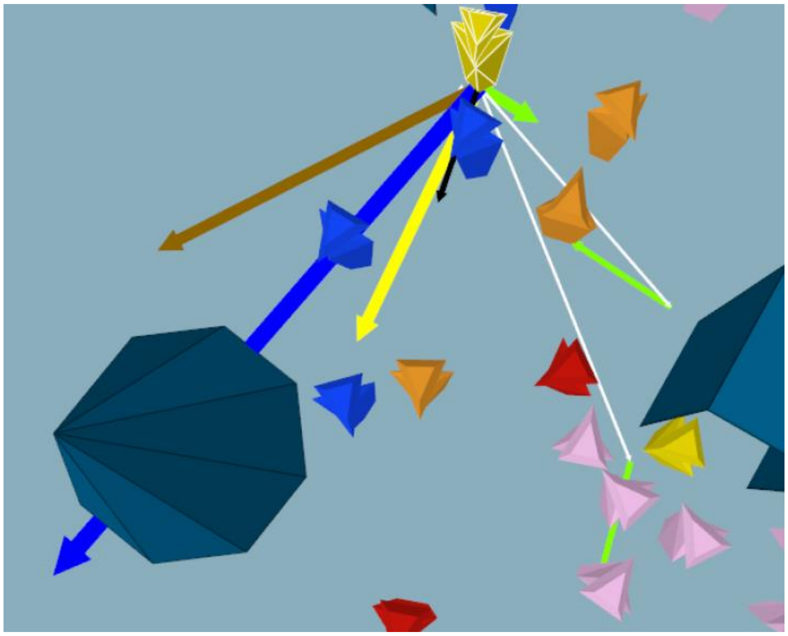

Figure 2.1: Social Forces acting on Agent in MassMotion [7]

The simulation splits up time into individual frames, which are calculated sequentially. Each of these forces is generated and summed for each agent to determine where the agent will move to in the next frame of simulation. Then, all agents are moved to their new positions and the process repeats. The model was employed in a computer program to simulate the flow of pedestrians, demonstrating its abilities to effectively model pedestrian flow [20].

Today, the use cases for modern pedestrian software can be very diverse, including fire safety, egress, circulation, and wayfinding. Similarly, the software can be used to model a variety of environments, including stadiums, theaters, skyscrapers, and transportation terminals. Of these, Public Transit terminals are one of the most common use cases [21]. Oasys MassMotion is one software in use for pedestrian modelling and has been used to help model pedestrian movement in several environments including Toronto's Union Station [22]. This program makes use of a modified Helbing-Molnar Social Forces Model [7], with all potential forces described in Table 2.1 below.

Table 2.1: Social Forces Model Component Forces (Adapted from [7])

Component Force	*Colour*	*Description*
Goal	Bright Green	Attractive force moving the agent towards its goal/target at the desired travel speed
Neighbour	Bright Yellow	Repulsive force from each neighboring agent (Maintains separation between agents)
Drift	Purple	Repulsive force moving agent in direction of preferred bias when faced with oncoming agents
Collision Veer Force	Turquoise	Repulsive force to prevent anticipated collisions with neighbouring agent

Collision Yield Force	Orange	Repulsive force causing agent to slow down to avoid collision with neighbouring agent
Cohesion	White	Attractive force moving agent towards centroid of agents with similar goals/targets
Marshal	Grey	Attractive force pushing agent towards middle of target when approaching
Corner	Brown	Repulsive force allowing agent to navigate corners
Constrained Net Force	Blue	Resulting net force
Constrained Velocity	Black	Resulting velocity

The speed at which the agent moves to its next location is dictated by a version of Fruin's Level of Service Model. This model is derived from Fruin's Level of Service work [3]. MassMotion applies a percent speed reduction based on the level of service. An example using the default mean values for the Fruin Commuter profile is shown below in Table 2.2.

Table 2.2: MassMotion Fruin Commuter Mean Walking Speeds (Adapted from [7])

LOS	*ft/min*	*m/s*	*Ratio of Maximum Speed*
A	265	1.35	1
B	260	1.321	0.963
C	250	1.27	0.941
D	240	1.219	0.904
E	225	1.143	0.844
F	150	0.762	0.563

It should be noted that MassMotion is far from the only pedestrian modelling software available; Other softwares and agent-based models also exist and are in use, including LEGION, VISWalk, and Pathfinder. While the principles of inputs remain the same, they may be driven by different algorithms which are beyond the scope of this project.

2.2 Verification and Validation Needs

The balance of each social force is delicate and must be tuned to ensure proper performance that meets industry standards. As fire safety is one key area of applicability for pedestrian modelling, MassMotion was verified against International Maritime Organisation (IMO) 1238 and National Institute of Standards (NIST) Technical Note 1822. These tests verified that the theories within these standards were correctly implemented in MassMotion, with results in accordance with expectations [23]. Validation simulations were also performed against real-life data and scenarios including route choices in a train station as well as flow rates and egress times in high rise evacuations, to demonstrate the differences between the model results versus real world data. While the testing and validation process is thorough, some tests including group behaviour could not be performed as MassMotion did not have the ability to directly represent the required test. Furthermore, there are multiple sources of uncertainty associated with the modelling process, including variability, uncertainty, and a lack of knowledge regarding physical behaviour, selection of input data parameters and the model itself. The verification and validation report states that under specific engineering applications, particularly for evacuation, the modeller should determine whether the alteration of default parameters may yield more probable predictions [23].

MassMotion has been under development for several years and continues to evolve, with the latest developments introducing social distancing measures [7]. As pedestrian microsimulation developers strive to keep making improvements to the accuracy of their models, more validation data is needed. An article published in Fire Safety Journal reviewed existing knowledge of population demographics and crowd dynamics and considered its implications for pedestrian modelling. Of particular interest, is how current models fail to account for the changing characteristics of the population. A review is provided of the background of evacuation calculations, including flow rates and the use of flow and time. Population demographic trends are also reviewed, with reference to an aging society and the obesity epidemic. The impact of age and body size on crowd speed and flow is discussed, and a series of sources on these topics are presented. Those authors emphasized the need to use current data in the demographics of the population for an evacuation model, accounting for the increased proportion of elderly and obese people, suggesting that commonly used flows may be over predicted by up to 36%. [24]

A literature review highlights challenges being addressed by researchers and modellers by reviewing the PED2010 proceedings and the Traffic and Granular Flow 2013 conference abstracts [25]. Six generic problem classes were determined, including (but not limited to) pedestrian dynamics of actor types which examined demographic differences, decision-making which examined evacuation and route choice decisions, and modelling of pedestrian dynamics which examined walking speeds, pedestrian flows, etc. Each class tabulates the reviewed documents, grouping them by subject. Several gaps were identified in this review, including route choice and movements on a larger, 'master plan' scale and accounting for aspects like walkability, vitality, safety, and land use. Also identified was a need to understand the flow through 'holistic' built environments where movement is driven by a process or procedure in a business. Finally, there is interest in wayfinding metrics and the effect of easy wayfinding on route choices and pedestrian dynamics [25].

To evaluate the effects of different pedestrian walking speeds on model results, a modelling study involving a stadium was performed [26]. The author of this thesis co-authored the conference paper, and the fulltext has been supplied as Appendix F. 4 egress scenarios were modelled, using default, average, observed, and forecasted population demographics. The movement speeds for these demographics were taken from manual observations of pedestrians in and around the stadium. The results showed differences in the egressed populations of up to 23% between the default and forecasted population demographic models. This demonstrated how models built with the default profile may underestimates egress times and how different demographics can have an impact on model results. Thus, it is highly important to consider a realistic variety of user demographics and their walking speeds in pedestrian models.

2.3 Modern Transit Terminal Design Guidelines

Modern transportation terminals are designed in accordance with several design guidelines. These help provide a minimum standard which buildings must adhere to, either to meet company/customer requirement, or to satisfy legal regulations. Station design requirements may vary between different countries and railway companies, but passenger flow remains an important topic.

While station design requirements may vary between different projects and different locales, all station designs should consider the flow of occupants. This is generally done in the early design stages. In Ontario, Metrolinx's design guidelines [27] call for a passenger flow modelling report at the 30% design stage, and a consideration of pedestrian flow principles in the 10% design stage.

The National Fire Protection Association (NFPA) publishes codes which govern in Canada for fire safety design. NFPA 130 sets out minimum requirements for both platform and station egress times, as well as occupant loading scenarios for emergency evacuation [28]. This includes an egress time requirement of 4 minutes to evacuate platforms, and 6 minutes for an occupant to reach a point of safety from the furthest point on a platform. Under NFPA 130, the occupant load assumes the simultaneous arrival of a train on all tracks plus the load of all entraining passengers, based on peak period ridership projections. Notably, NFPA assumes a maximum egress speed of 37.7 m/min (0.62 m/s) on platforms, corridors, and ramps, and egress speeds on concourses and other lower-density areas is 61 m/min (1.01 m/s). There are no provisions for specific impairments or other effects, but these values are also intended for use in hand calculations.

In the UK, the infrastructure provider Network Rail has documented design guidelines for design [29] [6] which considers predicted future demands factoring in future origins, destinations, and travel patterns for both travelling users and non-travelling users. Stations should therefore be designed to minimize crossflow and ensure that flow of pedestrians in the future is sufficient. Pedestrian modelling software is encouraged for the evaluation of movement and capacities, including at entrances and exits, around stairs, escalators, and elevators, at ticket offices, ticket gates, and on platforms and corridors. Scenarios including evacuations and system delays are also recommended for modelling and evaluation. As of 2011, LEGION was the preferred software to use, but the principles can also be applied directly to MassMotion with input data including CAD drawings to create the 3D virtual space, passenger Origin-Destination demand data to generate pedestrian traffic, and walking speeds that consider the population that the station will serve. Network Rail's guidance does consider that different station users may have different space requirements, and that speed may be affected by multiple factors including age, gender, physical condition, trip purpose, familiarity, trip length, and encumbrances such as luggage. Environmental characteristics including crowd density, walking surfaces, and weather conditions are also mentioned to play a role as well. However, the guidance acknowledges that the effects of many of these factors cannot be modelled, with wheelchair users and groups being given as examples. The guidance instead generalizes the population to move between 0.8 m/s and 1.8 m/s, with an average of 1.5 m/s for fit healthy adults and those with mobility impairments at around 1.2 m/s and encourages that the proportions of different passenger types be considered where possible. Model outputs for evaluation include Fruin's Level of Service Heatmaps, space utilization maps, flow rates, and pedestrian travel times. The model must also be validated including a comparisons of congestion levels, journey times, and flow rates. Variations between the model and expectations should be no more than 10% to be considered valid.

The American Public Transit Association published Universal Design Guidelines for North American transit facilities, a comprehensive document which examines the needs of station users following Universal Design principles [30]. There are several types of users, with a sample listed below in Table 2.3.

Table 2.3: Station User Types (Selection from [30])

User Type	*Description*	*Movement Speeds from Design Guidance & Default Parameters (m/s)*
Frequent Users	Familiar with the location, transportation system, or procedures, but may still face challenges in negotiating unfamiliar stations or other systems.	1.35 [7] , 0.8-1.8 [6], 1.53 [5]
First-Time users	Unfamiliar with station or system in general. Universal design should incorporate clear station entrances, wayfinding, maps, information to help first-time users navigate the station, including the location of suitable vertical circulation if applicable.	1.35 [7] , 0.8-1.8 [6], 1.53 [5]

Users with luggage	Luggage may range from backpacks to multiple suitcases. Users with luggage may move more slowly, may need more physical space, and may be more distracted trying to make adjustments. They may also need different vertical circulation features including escalators, ramps, or elevators.	1.53 (Heavy), 1.32 (Large) [5]
Users with Personal mobility equipment	While wheelchair users may be one of the first things to come to mind, these users may also include strollers and carts. These users cannot use stairs or escalators, and instead need ramps and elevator for vertical circulation.	0.58 (Wheelchair), 1.37 (Child in pushchair/stroller) [5]
Users with Mobility impairments	Includes wheelchairs, scooters, walkers, crutches, canes, etc. May also include lack of stamina and may be temporary or permanent. Accommodations may include use of ramps/elevators, potential use of escalators depending on type of impairment, wider accessible routes, and minimal use of rough surfaces.	0.58 (Wheelchair), 0.80 (Permanent or temporary physical mobility impairments) [5]

The above list is not comprehensive but demonstrates some of the diverse populations using transportation terminals and some of their potential requirements. Transit facilities should strive to accommodate all users, and the modelling should also reflect the users that the facility serves.

2.4 The Need for Local, User-Specific Input Data

The default parameters supplied within pedestrian modelling software such as MassMotion are based off of studies carried out in specific environments. MassMotion includes profiles from three studies: the Fruin Commuter, PD7974, and LUL. The Fruin Commuter was taken from Fruin's studies of pedestrian flow in New York City [3]. PD7974 was taken from the British Standard 7974, a British standard with a framework for developing fire protection methodology [31]. Finally, the LUL profiles are a series of different movement profiles taken from Transport for London's guidance for pedestrian modelling of London Underground facilities, and include mobility impaired, wheelchair, adult with child, and various sizes of luggage [5]. Each profile is a normal distribution representing walking speeds for each type of person, except for those with luggage in the London Underground profiles. This provides users with input data for general use, although in some cases the validation document does call for more accurate movement speed data [23]. However, the movement speeds and decision-making processes of pedestrians may vary depending on locale.

There are several human factors which may play a role in how each person may move or behave. Even in the infancy of pedestrian studies, researchers from London Transport in 1958 noted that their experiments done at a Boys' school with students resulted in different speeds and flows than what was measured in their subway corridors with passengers [16]. The type of facility may also play a role, as Fruin's original studies revealed different walking speeds in a bus terminal versus a railway station [3]. Differences may also exist between different countries, as highlighted by a literature review of empirical data. The study found significant differences between the unconstrained walking speeds of pedestrians in different countries and environments. Overall, the mean speed may differ by as much as 48% between studies in different locations, countries, and continents [32]. These theories are backed by a more recent study which examined several different potential factors in a literature review. The study concluded that while current profiles are a good estimate, providing an average walking speed for a particular unstudied location is difficult as it can be influenced by many factors, some of which are displayed below in Table 2.4 [33].

Table 2.4: Influencing Factors on Pedestrian Motion (Adapted From [33])

	Static Influences	*Dynamic Influences*
Endogenous Influences	**Physical pedestrian properties** • Age • Gender • Height • Weight • Disabilities • Luggage **Cultural Influences** • Social Status • Cultural environment • Size of settlement	**Emotional Influences** • Character, temper, mood • Time pressure • Trip purpose
Exogenous Influences	**Facility Properties** • Inclination of ramps, stairs • Moving speed of escalators/moving walkways • Street width • Walking surface quality	**Environmental Influences** • Time of Day • Weather & Temperature • Group Size • Pedestrian Density • Crossflow • Walking trip length • Transfer time at railway stations

On a more local level, attempts have been made to model various aspects of Canadian transit terminals. Siva Srikukenthrian’s thesis [34] focused on the crowding levels and route choices made by subway passengers during disruptions with a focus on transfer stations. The researcher found that there was an inherent lack of any local Canadian data available for their model, and thus had to resort to their own data collection. They noted that there was no available software to automate the process, and used video collected from cameras that they had set up to count passengers climbing or descending in 10-second intervals. Their methodology also involved counting persons of restricted mobility as a single category including those with heavy luggage or other mobility impairments. In other cases for determining waiting locations, they were required to use manual counting in-person to count the flow of passengers. Fatally inconsistent errors in this process were found from one set of data, resulting in the discarding of 1 of the 16 sets of data collected.

Differences in behaviour for pedestrians with luggage was studied in 1980s in two Canadian airport corridors, examining the effect of passengers with suitcases and luggage carts [35]. While the study found no differences between luggage, cart, or unencumbered free-flow speeds, significant differences in space requirements and headways were found, with more space required and lower headways for luggage-laden passengers.

A recent study in a Chinese laboratory environment showed that there were not always significant differences in movement speed within a group of luggage-laden and unencumbered people, but that the positioning of luggage-laden people within a crowd affected the walking trajectories and distances to the walls within a narrow passageway [36]. These distances increased when the pedestrians were running, and the suitcases were more likely to be dragged behind than pushed in front when running.

A more recent case study at a bus terminal in Malaysia examined the walking speeds of pedestrians with and without luggage, finding slightly slower walking speeds for pedestrians laden with luggage, with a difference of around 0.1 m/s [37]. The impacts of luggage on pedestrian movement is not just limited to corridors, as another recent study examined the at effects of luggage on passengers boarding and alighting from trains, as well as the associated station dwell times [38]. The study found that passengers with large items of luggage required almost twice the amount of time when boarding or alighting from trains. While these studies may be useful for determining pedestrian behaviour within corridor or platform environments, further exploration regarding the effects of luggage on behaviour such as route choice and waiting areas is needed, particularly in more open spaces such as arrival/departure halls.

These studies highlight the differences localized and user-specific factors can have. To further capture and consider these factors in modelling, walking speed data collection is needed.

2.5 Modern Technologies and Developments

There have been several studies done in the past few years to collect pedestrian speeds and trajectories using a variety of techniques and technologies. One method involved the use of cameras mounted high above the area to be analyzed, which gave fairly effective results for pedestrian counting, but movement speed generation was limited to manually timing the movement of each track between two lines [14]. A more recent study mounted cameras directly above the area to be analyzed and could track pedestrians automatically if a marker was applied to the pedestrian's heads. Alternatively, stereo cameras were able to provide depth perception and thus could autonomously detect and track pedestrians without user input [39].

In Australia, a project called Dwell Track was undertaken in which 3D infrared cameras were used to monitor passenger numbers and track passenger movement on station platforms [40]. This required the mounting of external equipment but could also broadcast to mobile devices for staff members to monitor rail platforms in real time. This automated process requires wired mounting and installation and does not provide demographics data. Although the anonymized data may pose some challenges for detailed data collection, this does allow Dwell Track to be used in locations with stricter privacy regulations. Additional papers have been published by the researchers which may be of use both in Dwell Track and for the development of other tracking applications. These include an Adaptive Counting Convolutional Neural Network for the purposes of pedestrian counting and density estimation [41], an application of the technology to examine pedestrian route choice on a passenger rail platform [42], and an estimation of pedestrian density at further distances using Deep Learning [43].

Another alternative is the use of LIDAR cameras to automatically track pedestrians. In this case, LIDAR sensors generate point clouds showing the distances to surfaces surrounding the camera, creating a 3D point map of the environment. Pedestrians can be identified from the background using software and software development kits, and tracking can be done on the identified persons [15]. Much like Dwell Track, the sensors cannot record faces or other personally identifying information, and thus could be used in more privacy-sensitive or restrictive environments.

While automated systems can be potentially quite efficient in collecting pedestrian speeds and trajectories, alternative methods with more manual intervention are also possible and come with their own benefits. Larsson & Friholm of Lund University used a software called Kinovea to track pedestrian motion, including walking speed and body movement in a lab environment [44]. Their results were compared to an automated motion tracking system which required the participants to wear tracking markers, to determine the effectiveness of each system for a detailed analysis of limb motion, walking speeds, and separation between pedestrians. In their conclusions, they compared the two processes, as displayed below in Table 2.5

Table 2.5: Video Analysis VS Optical Motion Capture Methodologies (Adapted from [44])

	Video Analysis	*Optical Motion Capture*
User friendliness (Preparation, Collection, Analysis)	High	High
Economical Aspects	Cheap even if hardware needs to be purchased	Expensive if hardware investment needed
Data Accuracy	Depends on sampling rate	High, Sampling rate is 100 measurements per second
User Dependency	High, everything from collection to analysis has user dependent aspects	Low, only preparation has user dependent aspects
Can handle obstructed markers	Markers can be manually estimated by researcher	Yes, but only if obstructions are for short periods of time
Can analyse without the use of markers	Yes, but accuracy will be lower compared to marked areas	No
Can be used for realistic crowd investigation	Yes, but accuracy of results may be negotiable	No, markers would be obstructed for too long
Time Consuming: Collection	Depends on number of participants and tests	Depends on number of participants and tests
Time Consuming: Analysis	Yes, even if analysis is automatic	No, Analysis is completed during the experiment

While the automated optical motion capture method demonstrated higher data accuracy, lower user dependency, and faster analysis, it was also found that there were drawbacks which made the method less effective for crowd investigations. The costs of the equipment were significant and applying any form of marker to a general crowd was unfeasible. Video tracking took longer but was less expensive and with a high framerate could be used in a realistic crowd investigation [44].

2.6 Conclusions

While the field of pedestrian flow studies is relatively old, new technologies have enabled the production of pedestrian modelling software to simulate the flow of pedestrians in buildings and optimize plans for the built environment. Recently, there have been a large number of studies on pedestrian movement and motion. This is a complex field to study as results may be highly localized and thus theories may need validation when applied in other areas.

Several methodologies and technologies have been developed for tracking pedestrians, including mounted cameras with automatic tracking, lidar, infrared, and motion capture. Larsson & Friholm note that the manual video analysis was highly user-dependent and slower [44]. However, this provides an opportunity for additional user input and thus forms the basis for this project and thesis. It was noted through all of the automated methods that they all examine the population as a whole. One of the disadvantages of the reviewed systems is that the automation removes the potential for more detailed analysis of specific demographics, actions, or other conditions which may impact the recorded movement speeds.

There is thus a knowledge gap in pedestrian tracking methodology, in that no software can provide pedestrian tracking which can then be categorized into distinct profiles for more detailed analysis of individual pedestrian types and behaviours. This is especially important as modern transit facility guidelines look to address specific types of transit facility users. A software solution combining the more precise video analysis of automated tracking and the detail of manual tracking may be an effective tool for generating and analyzing new movement profiles for pedestrian microsimulation.

Chapter 3: Software for Observing Behavioural aspects

3.1 Analysis of Pedestrian Trajectories Using Computer Vision Software

To address this missing combination of manual tracking and precise automatic video analysis, a new methodology was devised. The methodology makes use of computer vision software, augmenting it with a post-processing program to produce statistical distributions of movement speed data. This section covers the background, development, and validation testing for the new methodology referred to herein as Semiautomated Tracking.

3.2 Kinovea Background

Kinovea is an open-source kinematics analysis software intended to analyze movement in sports from video recordings [45]. The software is able to track the movement of selected points and make corrections for camera perspective angles and scaling to output distances and instantaneous speeds. This also makes Kinovea a viable candidate for pedestrian tracking and analysis, as performed previously by Lund University researchers (see [44]). However, that study does note that analysis is highly user-dependent and time consuming, as each tracking point must be manually specified. The Lund study also compared Kinovea with Optical Motion Capture technology, which, despite being faster and less-user dependent, was found to be less practical for use in crowd analysis as Motion Capture relied on the tracked persons wearing marker pads for tracking. As Kinovea tracks objects (or in this case people) frame-by-frame, it is useful in scenarios where people may not have a defined start and end point for tracking. The requirement for users to manually specify the point to track does open the door for manual tagging of demographics, which allows for demographic-specific analysis. The main tools and interface for Kinovea are shown below in Figure 3.1. The image has been annotated to provide a description of key components used for the methodology, with the legend provided in Table 3.1:

Table 3.1: Kinovea Interface Annotations Legend

Annotation #	*Item*	*Description*
1	Main Video Window	The video is played and edited in this window
2	Video Tracking Bar	The green blob shows where the current frame of the video is. The blob can be dragged to skip to any point in the video. Useful for moving between important moments in long videos
3	Playback Controls	From Left to Right: Skip to beginning, Go back 1 frame (Shortcut: left arrow), Play/Pause (Space Bar), Go Forward 1 Frame (Right Arrow), Skip to End
4	Speed Slider	Sliding this left slows video playback down, sliding to the right speeds video up
5	Perspective Grid	Creates a grid for distance calibration
6	Frame Rate	Displays frame rate for profile generation
7	Working Zone Bar	Sets the start and end times for analysis. This will scale the video tracking bar accordingly

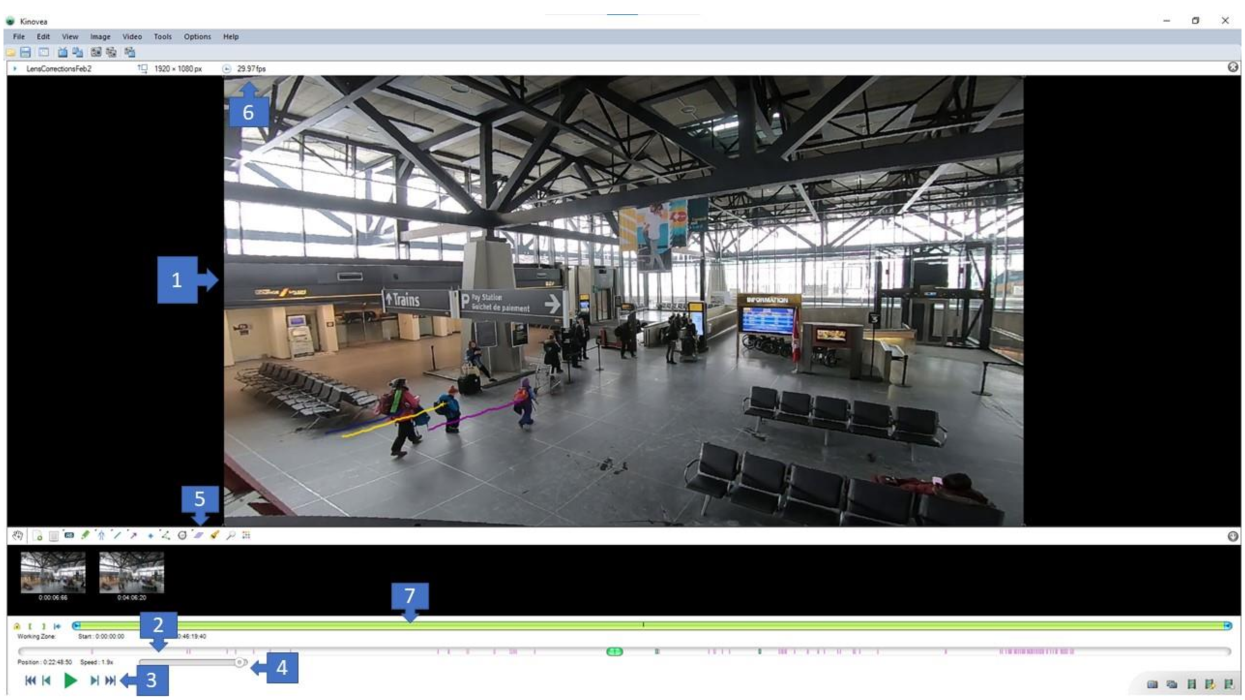

Figure 3.1: Kinovea Interface (See Legend in Table 3.1)

Kinovea's tracking algorithm uses the image within the previous frame to determine the position of the object in the next frame, trying to match the new candidate frame to the original. This is done by calculating a cross correlation coefficient between a potential candidate window in the next frame and the feature window of the previous frame. Each possible position is scored, and the best score is assumed to be the match for tracking marker to move to [46]. [1]

Kinovea and other video tracking technologies brings some advantages to the level of detail that can be applied to an analysis. While LIDAR and Infrared can be used in more restrictive environments, they may not capture finer details which may be useful for identifying demographics or other features such as disabilities, mobility devices, or luggage which may have an impact on a pedestrian's movement speeds, personal space, and/or decisions made. PeTrack is another software offering similar capabilities to Kinovea, analyzing video footage and generating pedestrian trajectories [39]. The software can perform automatic tracking through the use of markers worn by pedestrians, making it a good choice for lab experiments and controlled environments. A specialized stereo camera can also be used for automated tracking or for 3D environments. However, as detailed in Section 2.5, the automated system cannot distinguish between more detailed demographic features, much like LIDAR and Infrared. Kinovea's manual tagging and tracking means that this finer detail can be captured, and also does not have the marker or stereo camera requirement, making it possible to analyze footage taken from security cameras or other non-specialized cameras. However, Kinovea and the other softwares do not directly output statistical distributions of walking speeds, necessitating additional manual calculations and analysis. Each tracked pedestrian or object would need to be sorted or categorized if using a more

[1] While the use of video and software for analysis appears similar to Digital Image Correlation, this software and method allows tracking points to be defined at any time or location and for any duration.

detailed analysis method. In order to provide a faster method of analysis, additional software was developed to process the output data from Kinovea.

3.3 Profile Generator Development & Usage

To increase the speed of processing pedestrian motion videos in Kinovea, two pieces of software were developed. The first was an automation script which was designed to help automate the input processes, whereas the second was a post-processing software used to generate the statistical distributions taken from Kinovea's outputs.

To expedite the creation of tags on tracked people and objects, a custom AutoHotKey script was created. The script is used to automate keypresses and jump to relevant data entry fields, saving time by mimicking the inputs that a user would need to make, including several clicks and mouse movements. When this script is enabled, users are automatically prompted to enter a string of characters in the 'Name' field to represent the tags desired. The window automatically opens when a person is selected to end tracking, and the prompt window automatically closes and stops tracking once the tags are entered. The tagging window shows the person being tagged, but the user can also determine this while tracking is ongoing. The tags can be used to represent practically any attribute as specified by the user, as shown below in Figure 3.2.

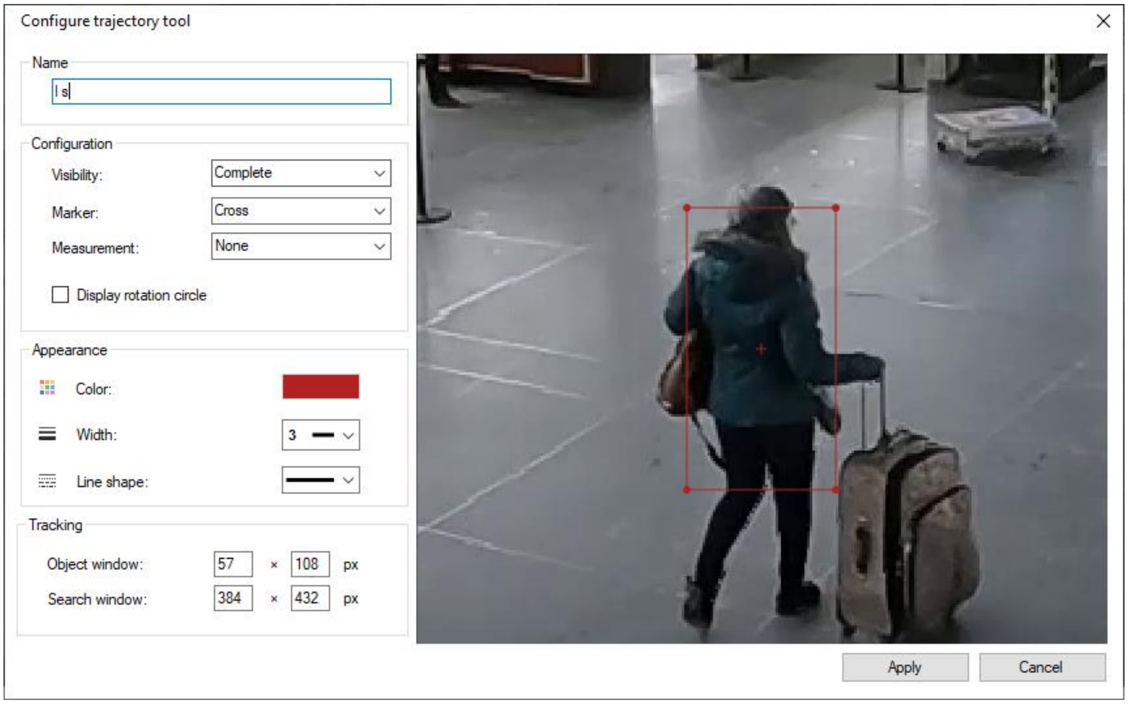

Figure 3.2: Tagging window in Kinovea (Tags l & s applied)

The operating procedure for Kinovea is as follows:

1. Load the video file and find a rectangular area of known dimensions at approximately torso-height
2. Ensuring that at least ¾ corners of the rectangular area are visible, then place a calibration grid such that the corners and edges align with the rectangular edge. Enabling the Coordinate system will extrapolate the grid to help with alignment.
3. Right-Click and select calibrate to open the calibration window. Enter the real-life dimensions of the grid edges in metres. This completes the calibration process.
4. Play the video, pausing when a person is found walking near the camera and calibration grid (Spacebar pauses and resumes playback). Right click on an area on the person's torso to start tracking. Note that height from the ground should be kept consistent for best results.

5. Resume the video to ensure that the tracking is working properly. If tracking is not working, press Ctrl-Z to undo the track and try again.
6. Once the person is nearing the edge of the video frame or area to be analyzed, Ctrl-Right click on them to open the tagging menu. Enter in the applicable tags, separated by spaces, then press enter. This will automatically stop tracking the person.
7. Repeat for all desired persons, saving periodically.

Kinovea can, by default, output the raw X-Y coordinates of each tracked object for each frame as a text file. A sample of one of these outputs is displayed below in Figure 3.3.

```
#Kinovea Trajectory data export
#T X Y
# s
0:09:00:74 6.73 -6.11
0:09:00:77 6.72 -6.14
0:09:00:81 6.71 -6.17
0:09:00:84 6.73 -6.23
0:09:00:87 6.74 -6.28
0:09:00:91 6.76 -6.35
0:09:00:94 6.80 -6.45
0:09:00:97 6.82 -6.52
0:09:01:01 6.84 -6.59
0:09:01:04 6.86 -6.66
0:09:01:07 6.87 -6.71
0:09:01:11 6.85 -6.74
0:09:01:14 6.84 -6.77
0:09:01:17 6.83 -6.80
0:09:01:21 6.80 -6.82
0:09:01:24 6.79 -6.85
0:09:01:27 6.78 -6.88
0:09:01:31 6.77 -6.92
0:09:01:34 6.77 -6.96
0:09:01:37 6.78 -7.01
0:09:01:41 6.80 -7.07
0:09:01:44 6.81 -7.14
0:09:01:47 6.82 -7.20
0:09:01:51 6.83 -7.26
0:09:01:54 6.82 -7.31
0:09:01:57 6.81 -7.36
0:09:01:61 6.79 -7.40
0:09:01:64 6.77 -7.44
```

Figure 3.3: Kinovea Raw Data Export (1. Tag, 2. Frame Timestamp, 3. X-Coordinate, 4. Y-Coordinate)

Custom scripts have been coded to collect and calculate movement speeds categorized by demographics tag. These scripts use the coordinate data and time between frames to calculate instantaneous and average walking speeds for each tracked person. The data is automatically separated and compiled according to each tag assigned in the tagging process. The script can also make adjustments for different camera frame rates, as well as detect and accommodate duplicated frames. The final output of the script is the average walking speeds and counts for each demographic analyzed, as well as an overall total. At the core of the script is the formula displayed below which computes the average speed across all frames for each tracked object.

$$S = \frac{\sum_{i=2}^{n} \frac{\sqrt{(X_i - X_{i-1})^2 + (Y_i - Y_{i-1})^2}}{T_i - T_{i-1}}}{n-1}$$

Where *S* is the walking speed, *X* is the X-coordinate for frame *i*, *T* is the timestamp at frame *i*, and *n* is the number of frames in which the person or object is tracked for. Excel VBA has been employed to accomplish this in an iterative fashion which automatically scales with the number of frames and number of people tracked. When used, the process is largely automated, with the user simply entering the framerate and selecting the output .txt file generated by Kinovea. Profile Generator then creates an excel spreadsheet with a table of processed data and the statistical distribution information separated for each tag. The program flowchart for Profile Generator is displayed below in Figure 3.4 and the corresponding VBA code is included in Appendix B. It must be noted that the code is still under development and should not be used in engineering practice.

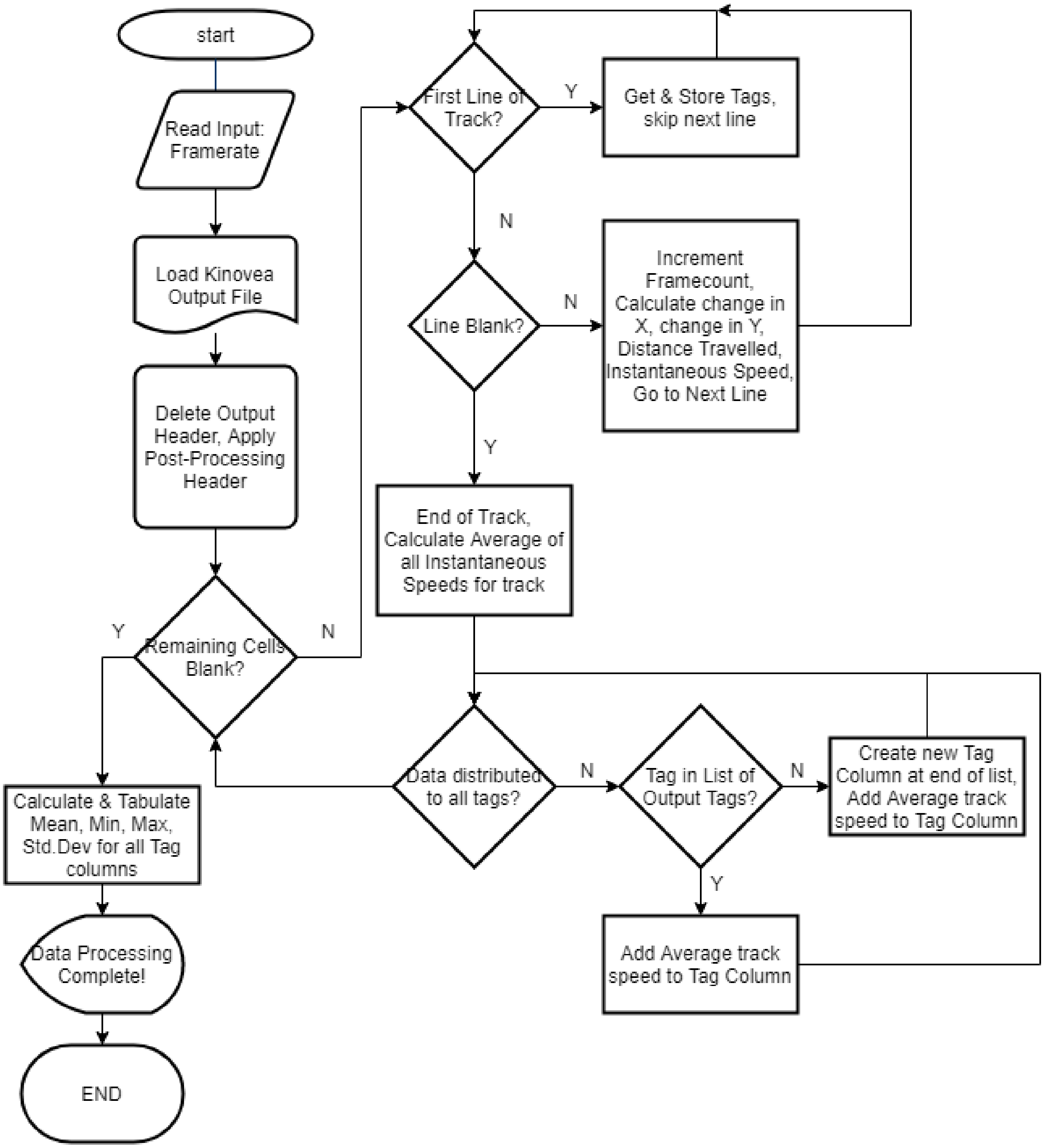

Figure 3.4: Profile Generator VBA Script Flowchart

Kinovea, as with all line-of-sight methodologies suffer from challenges in occlusion, when a person passes behind another person or object. Once line-of-sight is lost, it becomes very difficult or impossible for tracking to continue. Infrared and Lidar cameras are particularly susceptible as even transparent obstructions such as glass walls or barriers will block the cameras. When examining large crowds, the same occlusion issues exist as infrared signatures start to blend and shadows are cast by the first object in the Lidar's line of sight. Steep or near vertical camera angles may make it easier for individuals in denser crowds to be tracked, as shown by PeTrack's methodology [39]. One benefit of Semiautomated Tracking is that partial trajectories can be used, so if a person or object is partially occluded, tracking can be done during the non-occluded parts of the footage. Higher resolutions and frame rates also result in more detail which may improve tracking accuracy and abilities for denser crowds. In Kinovea, cameras are best set up with 4 measurable points visible in a rectangular shape, such as a floor tile pattern. This allows for calibration to correct viewing angles and distortion. The camera lens distortion must also be recorded and taken into effect using parameters set within Kinovea or through corrections applied to the raw video in video editing software.

3.4 Verification of Profile Generator Output & Limitations of Data Collection Techniques

The outputs from the Profile Generator and Kinovea are intended to act as the basis for future research both in this thesis and in future work. Thus, it is of high importance that the outputs of this new methodology are validated against real-world observations to ensure that the newly generated data is reliable. To check this, old video footage and walking speed data was re-analyzed under the new methodology to compare the two outputs. The old data comes from previous work analyzing pedestrian motion at a Canadian passenger rail station. The validation focused on passengers entering the station concourse via an escalator and proceeding to the exit of the station. The previous methodology and walking speeds were determined by

$$s = \frac{d}{t_2 - t_1}$$

Where s is the walking speed in metres per second, d is the estimated distance travelled between the escalator and the exit doors used, t_2 is the exit time, and t_1 is the entry time. This methodology has also been used for the collection of pedestrian speeds by previous researchers [13]. This older manual technique has a few distinct disadvantages; The distance travelled is only an estimate based on optimal linear distances although pedestrians may take less-than-optimal paths, the longer distances required manual tracking across multiple cameras, the final speed reported is an average over the entire distance which may be impacted by changes in walking speed, and finally some pedestrians took actions that disqualified them from manual tracking such as pausing to adjust bags, waiting for other group members, or visiting locations that were not the main exits. Of the 61 pedestrians on the route for this study, only 29 could be tracked using the manual methodology. In comparison, 53 of the 61 pedestrians were successfully tracked using the new semiautomated technique within a single video. The entry time and luggage carried by each pedestrian was used to determine which pedestrian was being tracked, as each pedestrian in the old data was assigned an agent number. This agent number was then applied to the tracked contour in Kinovea for direct comparisons between values. The statistical distribution for the pedestrian walking speeds is displayed below in Table 3.2:

Table 3.2: Profile Generator Verification Test Results

Data Source	*Manual Tracking*	*Semiautomated Tracking*	*Semiautomated Tracking (Direct Comparison with Manual Tracking)*
Mean (m/s)	1.04	1.15	1.15
Median (m/s)	1.05	1.18	1.11
Standard Deviation (m/s)	0.209	0.26	0.27
Population Tracked	29	53	27

The values produced by both methodologies are lower than the averages of the Fruin Commuter profile and Network Rail guidance and is higher than that of the NFPA 130 walking speed guidance. However, it does fit within the range of walking speeds for both the Fruin Commuter and Network Rail Guidance, with Semiautomated Tracking producing closer mean values. The new Profile Generator methodology produced walking speeds that were similar the manually tracked data, albeit slightly faster, with an average difference of +0.11 m/s and a maximum difference of +0.47 m/s which was noted for two pedestrians. In one case, the pedestrian slowed briefly to allow a group member to catch up but then resumed walking at a fast rate. Notably, the manual tracking method shows a 0.11 m/s difference in walking speeds between the two group members despite them walking side-by-side for the majority of their time in the concourse whereas the speeds generated by Semiautomated Tracking are nearly identical with only a 0.02 m/s difference. In another case the pedestrian took a longer path to avoid another pedestrian who had paused in the concourse to adjust luggage, thus travelling a greater distance than assumed by manual tracking. In both cases these may have played into error with the manual tracking resulting in a slower-than-reality walking speed in manual tracking, and thus the error lies within the manual tracking methodology. In most cases, the walking speed is lower than the speeds reported by Profile generator. However, the manual methodology once again assumes the most direct, optimal path with no slowing down, speeding up, or pauses. Thus, profile generator may actually be reporting a closer result than manual tracking.

There are also challenges regarding the video data used for collection, which applies not only to the validation but also future analysis of these particular videos. As the recordings used were not intended for use in Kinovea and Profile Generator, a heavy fisheye lens distortion effect existed on the original video data. A checkerboard pattern captured with the same cameras, combined with video editing software was used in an attempt to significantly reduce the fisheye effect. Work has been done by several researchers to automate this process, including Lee et al [47]. However, no freeware automated software was found that could generate acceptable results, thus this process was done manually. It is noted that this effect could not be fully eliminated, both here and in Lee et al due to approximation errors. As the video recordings predate the development of Kinovea and the need for a calibration grid, the initial grid corner locations needed to be estimated. In this case, the roof support column bases combined with movable rope barrier stanchions as seen in the videos were used to generate the x-y grid at approximately torso-height as seen in Figure 3.5. These approximations may have had an impact on the distance interpreted by Kinovea and Profile Generator.

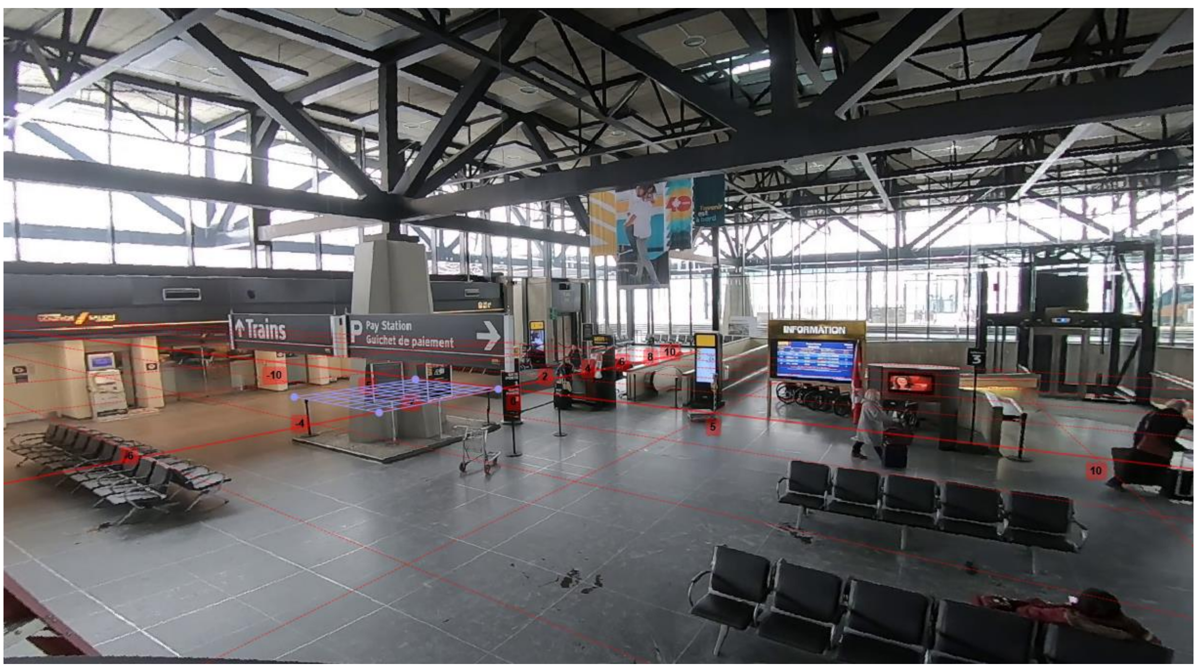

Figure 3.5: Calibration Grid for Validation Testing

The challenge in doing this type of comparison is that each method may have their own disadvantages and errors which may have impacts on the data. Without knowing the real ‘ground truth’ movement speed to compare to, the utility of this exercise is limited to saying that the new methodology produces similar movement speeds to the old methodology and thus should be acceptable for the generation of speed data. However, this data should not be relied upon until comparisons can be made to a real ‘ground truth’. While this was initially planned for this project, public health restrictions and challenges have relegated this validation experiment to future study. It is planned to run this study with multiple tracking technologies and with a speed sensor applied to people or tracked objects in a lab environment. By doing so, multiple technologies and methodologies can be evaluated simultaneously against known speed data.

3.5 Conclusions

To address the knowledge gap between fully automated and fully manual tracking techniques, a new methodology called Semiautomated Tracking was developed. This methodology combines the benefits of automated tracking software with manual tagging of each pedestrian. A post-processing script called Profile Generator was developed to augment Open-source kinematics software Kinovea to produce statistical distributions of data categorized by the assigned tags.

A previously completed study in a transportation terminal and concourse highlights the difficulties of using manual tracking, especially given multiple trajectories, longer distances, and manually untrackable trips. Validation testing on the same dataset shows a significant improvement in the number of people which could be tracked, while reporting similar albeit not identical walking speed distributions. However, the differences may be due to inaccuracies with the manual tracking method. As both manual tracking and Semiautomated Tracking may induce their own errors, further investigation is needed which was deemed to be outside the scope of this thesis.

Chapter 4: Collecting Pedestrian Behaviour and Motion in Transportation Terminals

Following the verification of Semiautomated Tracking, further analysis was conducted on the video data in the transportation terminal. To determine the impact of various aspects on the movement of pedestrians within the terminal, multiple key factors were considered and analyzed simultaneously.

4.1 Behavioural Aspects Based on Stimuli

Some of the key factors were inspired by a research project conducted in 2019 at a Canadian Tennis Stadium. That project was published and led by the author [48] and focused on stress states in different egress scenarios based on various stimuli. The subsequent subsections are a summarized excerpt from the paper where relevant towards addressing the theses main objectives. The full version can be read in Appendix A.

4.1.1 Site Recording Setup

One scenario covered a standard post-game egress of the stands, whereas another captured an unscheduled egress due to a sudden rainfall. Two GoPro Hero 7 cameras were set up at vantage points above the stadium to capture 1080p HD footage of stadium attendees as they moved towards the exits. These vantage points are displayed below in Figure 4.1 and Figure 4.2.

Figure 4.1: Tennis Stadium camera station locations and approximate field of view.

Figure 4.2: Still image of a utilized Centre Court camera illustrating an observed gate.

In both scenarios, Gates B and C (at the location of cameras A and B, respectively) were used to record the amount of people arriving at and departing from the gate every five seconds during the egress. The data from the camera footage was then used to develop graphical interpretations of the egress: the percent of the population egressed with time, and the flow of people per unit width of the gate with time. Additionally, records were taken to track exit usage by assigning the chosen exit to each spectator. While the camera angles, heavy lens distortion, high pedestrian congestion and significant changes in vertical positioning meant that Kinovea and Profile Generator could not be used to generate movement speeds, manual methods of observation were used to determine several other key factors surrounding the egress. The footage from these videos allowed for the generation of a timeline to highlight and compile key events during each egress and quantify re-occurring behaviours. Flow counts were also performed at the exits by counting the number of patrons passing through at approximately 5-second intervals which were added into the timeline after the flows were determined. CAD files provided by the stadium were used to determine corridor and exit widths, which were subsequently used to calculate flow rates in people/metre/minute.

4.1.2 Results

The standard post-game egress at the Tennis Stadium was analyzed in over 13 minutes of video footage. It is important to note that the video was recorded at the end of the second to last match so egress would be influenced by crossflow from other entering spectators. Table 4.1 lists the timeline and observed behaviours that influenced egress. The origin (00:00 time) is when the match had ended.

Table 4.1: Decisional Behaviours of the Standard (Post-Game) Egress

Time in videos	*Decisional Behaviours and Key Events Observed*
0:00-0:30	• Even though the match has ended and employees have opened aisle barriers, there are still spectators watching the court players. Main egress begins where spectators predominately exit the gate they entered. • At approximately 15 seconds 8% of the population is in movement, by 30 seconds this is 14%.
0:30-0:48	• Spectators begin egressing but some stop mid stairs to look at the court activities (1.5% of total population). These spectators loiter at the perimeter of the bowl again watching the court activities. Stairs begin to show congestion with starting and stopping of spectators.
0:48-0:58	• As this match has ended, a new match will begin in about half an hour, evidence of cross flow occurring with people entering.
0:58-1:48	• Players exit the court and applause stops, egress increases
1:48-3:48	• An interview begins of winning player shown on stadium screen, similarly before egressing people stop and watch the screen periodically. Some have not left their seats.
3:48-4:35	• Once interview ends, egresses pick up. This is the last game related activity. Peak flow occurs at 89 ped/min/m width.
4:35-7:06	• After peak flow, egress subsides. Announcer comes back on to announce winner and waive of prizes. This again results in a distraction of people leaving the stadium (loiter in the bowl and on the stairs), where 1.8% of the total population per stand some turn back. • Only 7% of those in attendance remain sitting and not in the process of moving by 4:35.
7:06-8:24	• Final acknowledgements by announcer.
8:24-13:05	• Gate usage is steadily decreasing from 20 ped/min/m to minimal.

For the rain evacuation at the Tennis Stadium, the total recorded egress was 2 minutes 55 seconds. Table 4.2 displays the timeline and observed behaviours which appeared to influence egress. The origin (00:00 time) is taken as just a few seconds before a formal announcement is made, because at this time, some spectators had already begun egressing.

Table 4.2: Decisional Behaviours of High-Motivation (Rainfall) Egress

Time in videos	*Decisional Behaviours Observed*
0:00 -0:08	• Rain approaches. Employees open gates at 0:00, where game is suspended by announcer at 0:03, rain encompasses stadium by 0:08. Evacuation is largely simultaneous at suspension announcement. • There are few (<10) who while seated pull out umbrellas, about 20 who do not have umbrellas stay seated. • Majority go to closest gate relative to seating.
0:08-0:19	• As congestion at some gates begins (climbing rapidly to 120 ped/min/m), there are 4.5% of the pedestrians that do not use the closest exit and switch gate destinations on their journeys. At this point, queuing develops at all gates. Queues range in length to about 5-10m. Queues are directed against the wall as there is some shelter there. • People are carrying possessions including food. • Elderly people seen clearing a path in queues with walking stick, hitting others out of the way. • At approximately 15 seconds 97.5% of the population is in movement.
0:19-0:20	• Rain intensifies. Spectators who remained seated without umbrellas begin to evacuate.
0:20-2:45	• At 0:20, peak congestion is seen which steadily decreases until the stadium bowl is empty at 2:45. Those with umbrellas remain committed to their seats.

Figure 4.3 and Figure 4.4 describe the percent population egressed with time and the flow of persons per minute per exit width with time for the standard and high-motivation egresses, respectively. The timelines can also be referenced with Table 4.1 and Table 4.2 above, for detailed time markers and event descriptors which correlate to the observed max peaks seen based on specific events seen in the stadium egress. Figure 4.2 is helpful for reference as it illustrates an observed gate.

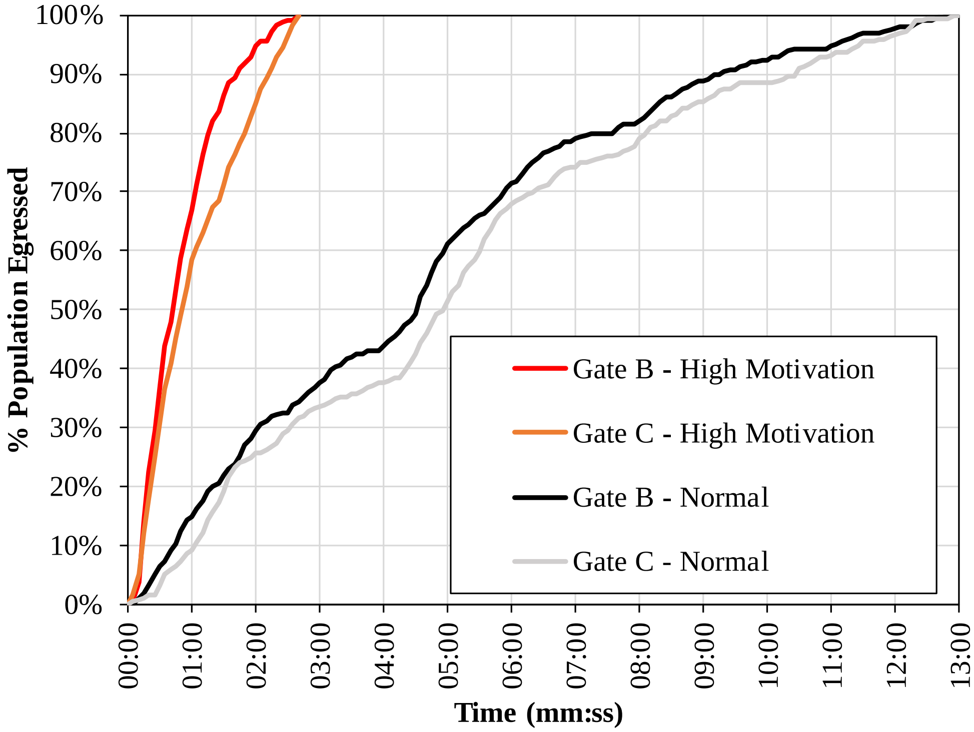

Figure 4.3: Percentage of population egressed for Normal and High Motivation Stimuli

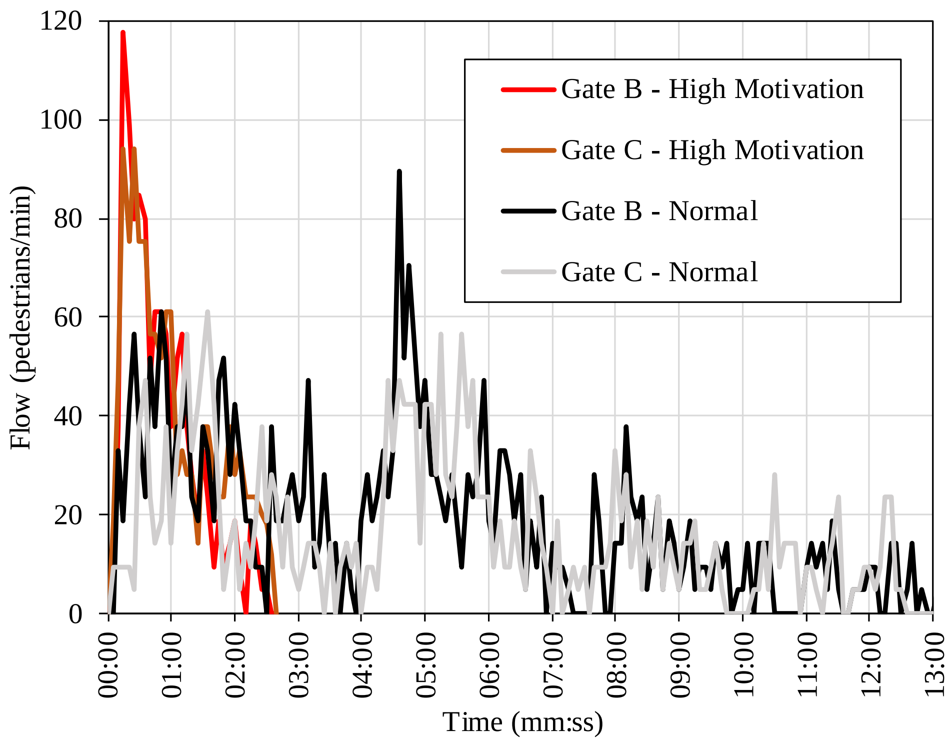

Figure 4.4: Flow at Gate for Normal and High Motivation Stimuli

4.1.3 Factors of Interest for Transportation Terminal Study

While the environment at the stadium was not conducive to pedestrian movement speed generation, it can be used as guidance towards different situations and their effects on pedestrian motion for examination in a transportation terminal. Urgency was the main focus of this study, as the rainfall scenario presents a different scenario with behaviour similar to a fire or other emergency. Through an observation of behaviours and flow rates, it was discovered that the high urgency rainfall scenario resulted in much higher flow rates and a significantly faster egress. There may also be higher-urgency scenarios for pedestrians moving in a transportation terminal, including late passengers trying to get to a boarding gate before it closes for departure, or passengers from a late arriving vehicle trying to get to their last-mile transportation quickly.

Behaviours also differed with a significant reduction in pre-movement time, with most of the attendees beginning their egress within 15 seconds of the start of rainfall, compared to just 8 percent of attendees beginning their egress following the end of a match. While a small number of stadium attendees did remain in their seats for a time before deciding to begin their egress, this doesn't compare to the vast majority of attendees which remained in the stands for considerably longer following a standard end-of-match. In some cases, those who remained and even those egressing were observed to carry out interim tasks such as observing post-game events on screens and speakers. A similar situation may exist in transportation terminals with some passengers remaining seated even following announcements calling for pre-boarding and queueing, and others potentially doing other tasks which influences their overall travel time through the station.

While not examined in detail in the paper, the stadium study also captured a variety of encumbrances which may have affected movement speeds. As mentioned in section 2.3, accessibility is highly important in transportation terminals as they are used by a diverse population. Encumbrances such as luggage are common, but accessibility and mobility devices such as luggage carts, strollers, and wheelchairs may also have differing considerations. The use of mobile phones or smartphones may also be investigated as an additional encumbrance.

These factors of interest were carried forward into the Transportation Terminal Study for further examination to determine if the same effects have impacts on the walking speeds of pedestrians.

4.2 Station Observations

The Transportation Terminal data was taken from a study which was completed in 2019. The data was initially recorded as part of undergraduate research work which precedes this project. The transportation terminal in question is an intercity railway station in the densely populated Quebec City-Windsor corridor. The station serves 2 routes, and at the time of filming saw up to 16 arrivals and 16 departures daily. While most trains terminate at the station, some trains to and from the east originate or terminate at a suburban station west of the city. No tickets are sold between the two stations, thus these trains count as an arrival or a departure only. The passenger platforms consist of 1 stub track and 1 high-floor platform on a through track accessible using doors on the east and west sides of the station, as well as 3 double-length platforms on through tracks which are accessed by an underground tunnel. The tunnel is accessed primarily using escalators which are reversed in accordance with passenger flow, but a spiral ramp and elevator are also available. Arrangements were made with the station’s owner and operator, VIA Rail Canada, to permit filming of passenger movements for a select few trains during expected busy periods. The original setup, procedures, and schedule are described as follows in a summarized excerpt:

4.2.1 Site Recording Setup

Although security cameras were present in the station, the poor footage quality was thought to pose challenges to data collection, thus additional cameras were set up to record passenger movements in the station. One concern was that passengers would notice the cameras and alter their behaviour as a result. In order to minimize the visibility of the cameras and avoid this effect, small action cameras were used. 1 GoPro Hero 6 Black camera, 1 Safari Action camera, and 3 GoPro Hero 7 Black cameras[2] were set up in strategic locations in the station. All camera positions and filming procedures were reviewed and approved by VIA Rail before the first day of recording. An image illustrating the concourse camera positions is provided in Figure 4.5.

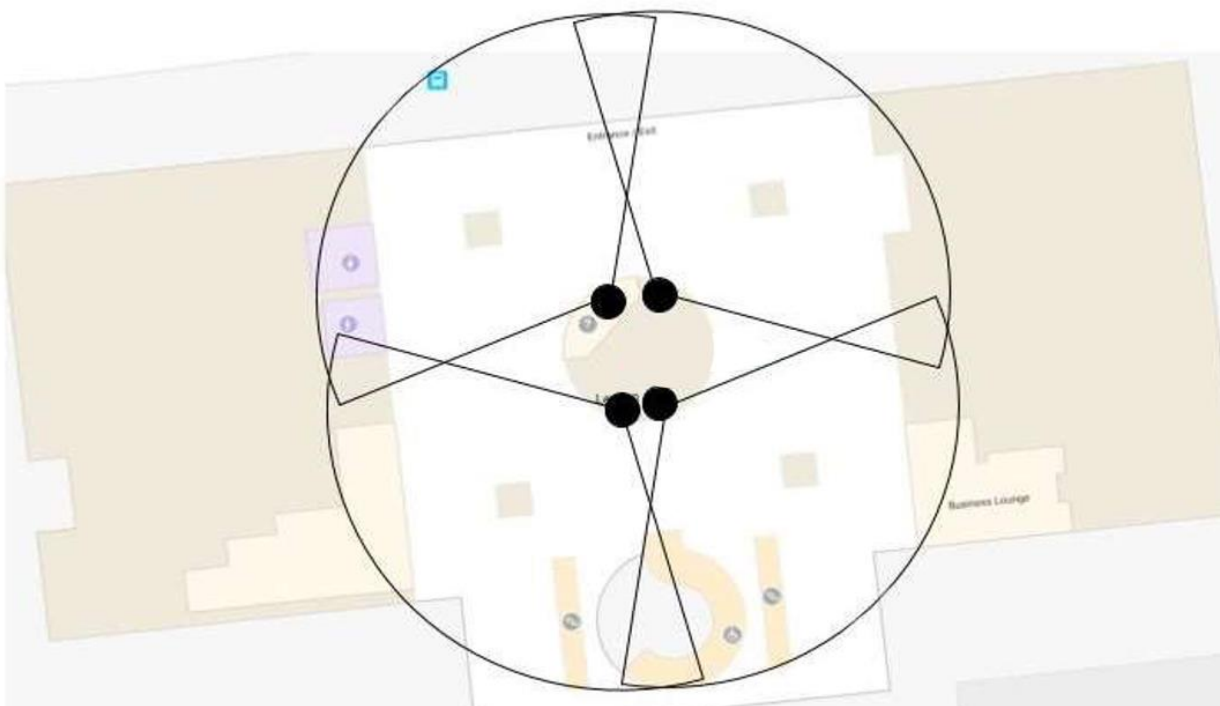

Figure 4.5: Camera Positions

[2] The models of camera were inconsistent due to the fact that some of the cameras were purchased at different points in time and thus were part of existing equipment.

4 cameras were used to record the station concourse, mounted using JOBY tripods placed on top of the rotunda which housed the ticketing office. These cameras focused on the boarding gates and the station entrance concourse. As illustrated in Figure 4.6, the cameras do not stand out when mounted on the roof, and do not attract attention when recording due to their small visual footprint. The front-facing recording lights were also disabled to further avoid attracting attention.

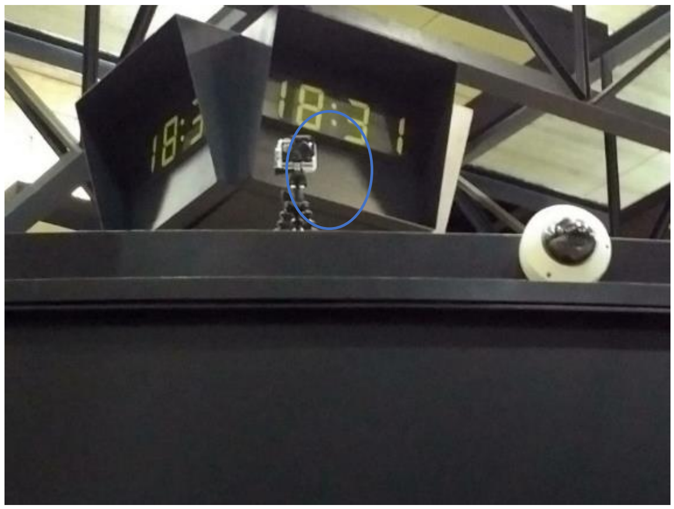

Figure 4.6: Camera mounted on Roof (Circled)

4.2.2 Filming Schedule

Filming took place on 4 days over 3 weeks by the author and an assistant. Two weekday evening filming sessions were done, plus two weekend mid-day sessions. Each filming day was centered around between certain times of interest, where there were multiple departures and arrivals within approximately an hour. Table 4.3 and Table 4.4 below summarized the intended days, times, and trains to be filmed.

Table 4.3: Scenario Outline

Scenario	*Recording Times*	*Arriving Trains*	*Departing Trains*
Morning	10:50 – 11:45	2 (11:04 & 11:29)	2 (11:20 & 11:40)
Afternoon	13:45 – 14:35	1 (14:15)	2 (14:20 & 14:30)
Evening	18:20 – 19:10	2 (18:46 & 18:53)	2 (18:26 & 18:55)

Table 4.4: Filming Schedule

Date	*Scenarios*
Saturday, January 19th	First Tests, Morning, Afternoon
Tuesday, January 22nd	Evening
Saturday, February 2nd	Morning & Afternoon
Tuesday, February 5th	Evening

4.3 Filming Analysis Parameters

In some cases, trains did not arrive or depart as scheduled, leading to deviations from the filming plans. This was carried forward to determine which trains would be analyzed for pedestrian flow.

The factors under consideration were taken from the factors of interest in Section 4.1.2. Each factor was considered individually unless otherwise stated, and pedestrians were tracked using the Semiautomated Tracking methodology. The factors under consideration, as well as the parameters to separate different types of passenger are as follows:

4.3.1 Urgency – Time Until Train Departure

The hypothesis of this factor is that as departure time nears, the walking speed of passengers increases. Station operations at major terminals in Canada utilize a queueing process similar to airports, where waiting passengers queue for ticket inspection before boarding. It is noted that movement speeds within the queue are impacted by queuing congestion, so general circulation and passengers moving to join the queue are taken as the baseline walking speed instead. As boarding commences, the queue dissipates. Passengers approaching the gate after the queue has dissipated (Usually 5 – 10 minutes before gate closure) are considered as late boarding passengers and are high-urgency. The analysis will be focused on a morning and afternoon with weather circumstances leading to a higher number of late passengers.

4.3.2 Urgency – Late Arriving Train

The hypothesis of this factor is that passengers arriving on a late train will walk faster than those from a train which arrives on time. The delays of each arriving train can be estimated based on the video file timestamps and train schedules. A train will be considered as on-time if arriving less than 15 minutes late, but the approximate delay will still be noted. Considering that significant delays were observed in the evening on one day of filming, evening data will be also considered for this analysis.

4.3.3 Accessibility

The hypothesis of this factor is that there is a difference in walking speeds for passengers who fall under the APTA's different station user types, and that Semiautomated Tracking can distinguish between these user types. Passengers will be analyzed and tagged according to luggage, family (I.E. In group with children), phone use, use of a mobility aid such as strollers and luggage carts, and presence of a mobility impairment indicated by crutches or wheelchairs. It must be noted that as this technique relies on visual analysis only and does not collect any information on the occupants, it cannot consider less visible or invisible disabilities. Also, as e-boarding passes can be presented on phones, boarding passengers cannot be considered for phone use.

4.4 Results and Analysis

Several train boardings were recorded and analyzed using Semiautomated Tracking to determine the movement speeds of passengers who arrived at the gate after the initial queue had cleared. In the footage, passengers can be seen approaching the gate at various speeds. To evaluate the differing factors, tags were applied to each tracking trail as shown below in Table 4.5. Multiple tags were applied simultaneously to maximize the depth of analysis while minimizing the number of data collection runs.

Table 4.5: Analysis Tags

Factor	*Tag Character*
Urgency	
Late Arriving Train	l
Arriving, On-Time train (Baseline)	a
Joining Queue, Late for boarding	b
Joining Queue following Announcement (Baseline)	q
Accessibility	
Large Suitcase/Luggage	s
Phone Usage	p
Family (I.E. in Group with Children)	f
Mobility Aid (Stroller, Luggage Cart)	m
Mobility Impairment (Crutches, Wheelchair)	i

Three recordings were analyzed in accordance with the tags presented in Section 4.3. Two recordings were taken on the same day and captured one arrival and one departure each in the Morning and Afternoon, while a third was taken a few days later and captured an evening involving 3 arrivals and 2 departures. To ensure a diverse set of data and minimize duplicates, only one camera for each recording was analyzed. The results of the statistical analysis as calculated by Profile Generator are displayed below in Table 4.6, Table 4.7, and Table 4.8. It must be emphasized that the methodology for collection has yet to be fully validated, thus the values presented should not be used for engineering applications; They are used here for comparison purposes only.

Table 4.6: Morning Results

Tag	*Arriving (On Time)*	*Queue*	*Boarding Late*	*Phone Usage*	*Suitcase*	*Family*	*Mobility Aid*	*Mobility Impaired*
Min	0.72	0.41	0.73	0.73	0.41	0.65	0.59	0.67
Max	1.88	1.34	3.73	1.20	2.45	1.82	0.80	0.67
Mean	1.16	0.81	1.60	0.93	1.10	1.12	0.72	0.67
Std	0.25	0.20	0.60	0.19	0.36	0.37	0.11	N/A
N =	62	24	34	6	45	12	3	1

Table 4.7: Afternoon Results

Tag	*Arriving (On Time)*	*Queue*	*Boarding Late*	*Phone Usage*	*Suitcase*	*Family*	*Mobility Aid*	*Mobility Impaired*
Min	0.37	0.63	0.77	0.72	0.60	0.84	0.63	0.37
Max	1.57	1.29	1.74	1.43	1.47	1.04	0.70	0.37
Mean	1.11	0.79	1.14	1.05	1.01	0.93	0.66	0.37
Std	0.28	0.24	0.26	0.26	0.23	0.11	0.04	N/A
N =	57	7	11	7	29	4	3	1

Table 4.8: Evening Results

Tag	*Late ~1h+*	*Late 20 Min+*	*Queue*	*Boarding Late*	*Phone Usage*	*Suitcase*
Min	0.71	0.97	0.56	1.08	1.03	0.67
Max	1.91	1.66	1.35	1.91	1.47	1.91
Mean	1.18	1.28	0.88	1.65	1.25	1.10
Std	0.26	0.20	0.16	0.39	0.15	0.29
N =	47	28	82	4	7	88

These datasets are further broken down and individually analyzed in the sections below.

4.4.1 Urgency – Time Until Train Departure

The examination of passengers arriving at the station shortly before train departure was primarily based on recordings taken on the Morning and Afternoon of February 2nd, 2019. The results and comparisons between the recordings are displayed below in Table 4.9. As mentioned in Section 4.3.1, the Queueing tag is assigned to those deemed to be travelling to join a queue or move from the queue to a gate, and the Boarding Late tag is given to those joining the queue or approaching the gate after the queue has dissipated.

Table 4.9: Queueing VS Late Boarding passengers Profile Distributions

	Morning		*Afternoon*		*Evening*		*Overall*	
Tag	*Queue*	*Boarding Late*	*Queue*	*Boarding Late*	*Queue*	*Boarding Late*	*Queue*	*Boarding Late*
Min	0.41	0.73	0.63	0.77	0.56	1.08	0.41	0.73
Max	1.34	3.73	1.29	1.74	1.35	1.91	1.35	3.73
Mean	0.81	1.60	0.79	1.14	0.88	1.65	0.86	1.50
Std	0.20	0.60	0.24	0.26	0.16	0.39	0.18	0.56
N =	24	34	7	11	82	4	113	49

On February 2nd, a higher than usual number of passengers arrived close to the departure of their trains, potentially due to a snowstorm which may have impacted traffic and road travel times to the station. It is noted that the station is not located in the downtown core and at the time had no rail transit link, thus most passengers arrived at the station by bus, taxi, or car from an adjacent freeway. This resulted in a higher number of late passengers observed during the morning and afternoon sessions. In the evening session from February 6th, severe departure delays led to a significant reduction in late passengers as most if not all would have still been waiting at the station well after the scheduled departure time.

Passengers joining the queues posed some challenges for tracking, including taking routes outside of Kinovea's tracking range, and being obscured partially or fully by the rotunda and other passengers. This was more of a challenge during the afternoon, where the flow of passengers joining the queue mixed amongst the flow of passengers who had just arrived from another train. However, an escalator breakdown during the evening session allowed for the analysis of a significant number of boarding passengers as they crossed the station to reach the alternative escalator.

Despite the different days, times, and conditions of recording, the data shows similar normal distribution parameters for queueing and late-boarding passengers respectively. Across the three trials, the mean speeds differ by a maximum of 0.1 m/s for queueing passengers, and the maximum speeds differ by only 0.05 m/s. The standard deviation also remains relatively low at 0.18 m/s, but this may be influenced by the more densely-packed and orderly queue observed during the evening session. The mean speeds for late running passengers is much higher at 1.5 m/s, which represents a 0.64 m/s difference, or 74% faster than the walking speed to join the initial queue. However, the behaviours of late passengers differs. Some continue to move at around the mean speed of those who joined the queue earlier, while others run significantly faster. The maximum recorded movement speed was 3.73 m/s. This high variability is reflected in a substantially higher standard deviation. The overall boxplots of the two profiles is displayed below in Figure 4.7

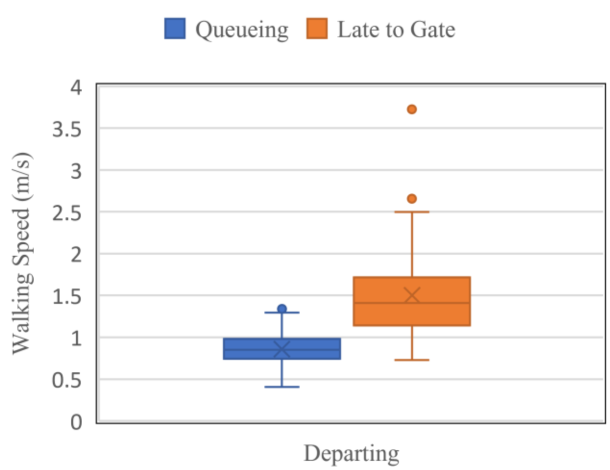

Figure 4.7: Departing Passenger Profile Boxplot

Overall, the result is in line with expectations set by the stadium observations. When presented with a more urgent situation, movement speeds are higher. In this case, the imminent closure of the gate may have been sufficient for passengers to move faster. The mean movement speed for late passengers is also 1.5 m/s, which precisely matches Network Rail’s expected walking speed for ‘fit, healthy adults’ [6]. While the queueing walking speed is also within Network Rail guidance, it is well below the expected walking speed. It is noted that a few passengers chose to run instead of walk at a faster pace. Some passengers started running after speaking with staff members, while others slowed down. In another case, a passenger started running once they noticed the (automatic) doors to the gate starting to close. More investigation into potential trigger stimuli for running in transportation terminals may be possible with this technology if needed.

There are a few other observed behaviours of note which may have impacted movement speeds and data collection. During the Morning session, an interesting self-organization phenomenon presented itself for boarding passengers. One passenger moved to the queueing area before boarding was called and was slowly joined by other passengers queuing prematurely. The queue was not formed in the correct location, and once boarding was announced, the passengers were directed by staff to the proper queuing area. It is noted that the area in which the queue formed tends to be used as a corridor for passengers on arriving trains. Figure 4.8 below shows the location of the original, premature queue and the queue in the designed location.

Figure 4.8: Premature Queueing before (Left) and after (Right) being directed by staff

Passengers also do not all move to queue at the same time, even when an announcement is made. Some remain sitting in the waiting area until the queue shortens, as illustrated below in Figure 4.9. This is consistent with observations made during the stadium study, where not all occupants moved to egress immediately, unless there was additional stimuli or situation to warrant a faster egress.

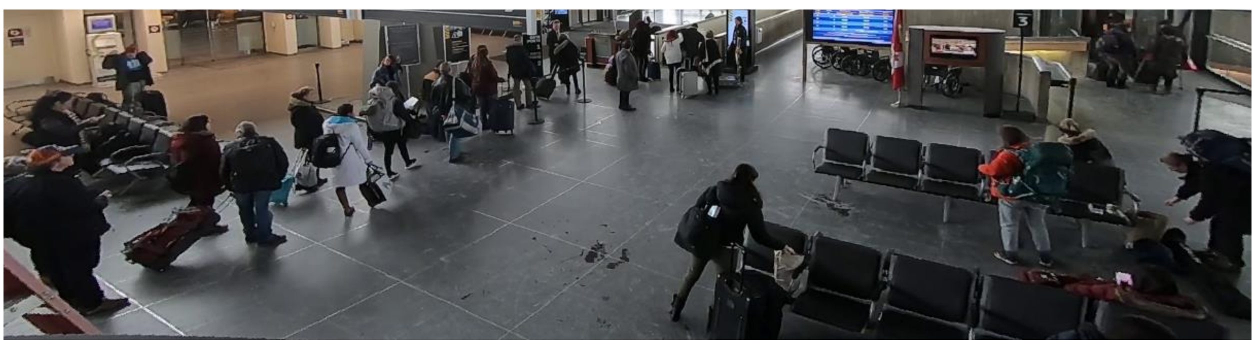

Figure 4.9: Passengers in waiting areas preparing to move to queue well after first boarding call

In addition, a few other occasional behaviours were observed from late passengers, including running to the gate first without baggage to request that the gate be held, followed by a trip to the curb and back to retrieve luggage. In another case, a large group was observed arriving and boarding quite late. Finally, some passengers were observed arriving at the gate after it had closed, as seen in Figure 4.10. These passengers, some of which had missed their trains, tended to have higher movement speeds.

Figure 4.10: A passenger runs to the boarding gate after the gate closing time, Gate was kept open by staff.

Finally, some late passengers approaching the east gates from the west side of the station appeared to be holding paper cups or other food bags, as seen below in Figure 4.11. This is notable as at the time of recording, a coffee and snack stand had recently opened in the west side of the station. While more investigation is needed, the presence or introduction of additional concessions and amenities in the station may have played a role in the late boarding of some passengers.

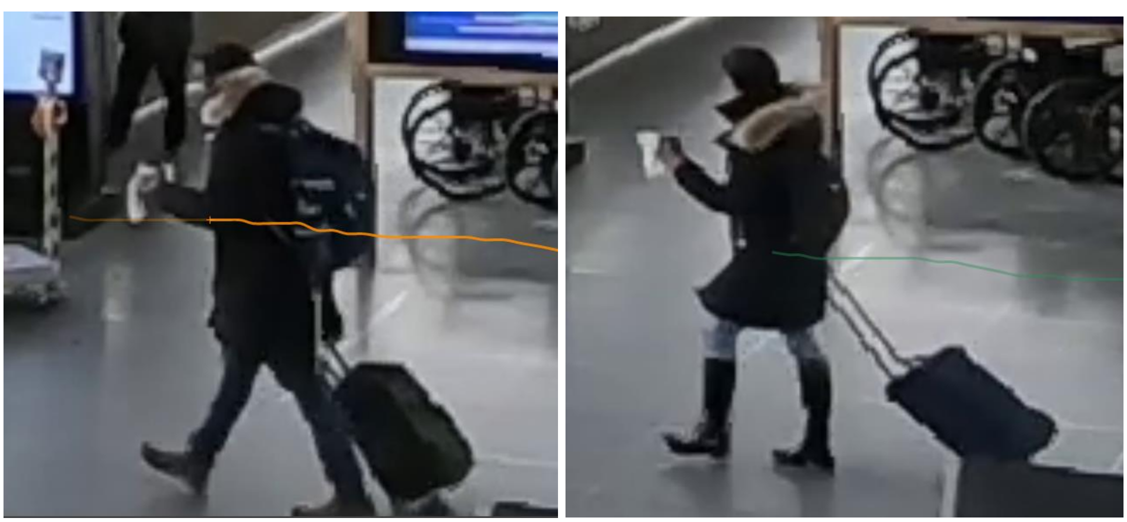

Figure 4.11: Passengers late for boarding holding coffee cup & food bag

In conclusion for this section, running late to board a train appears to result in an increase in walking speed. However, the speeds are highly variable, as are the behaviours and conditions associated with passengers who run instead of walk. More investigation is needed as to the stimuli and causes that induce additional behaviours such as running or becoming late in the first place.

4.4.2 Urgency – Late Arriving Train

The examination of passengers arriving on trains with various stages of lateness was conducted based on 4 arrivals recorded in the analysis footage. The footage is identical to what was used for evaluating boarding. The base scenario was taken from passengers disembarking from 2 trains in the morning and afternoon, each of, which arrived approximately 10 minutes late.

The examination for passengers arriving on late trains was based on recordings taken on February 5th, 2019. The schedule intended to capture the arrival of one train the east and another from the west, as well as the departure of one east and westbound train. However, on that day there were severe delays on the line coming from the west, resulting in the significantly late arrival of two trains. As these trains started to operate very close to each other, the train operating company decided to join the two trains together. This procedure occasionally happens so that 2 trains can move through the network while only occupying a single signal block. Some trains are scheduled to operate together and then split at a station to go to different destinations, but joining 2 trains together is more rare. At approximately 6:50 PM, the trains arrived, with a delay of about 2 hours and 15 minutes for one train and 52 minutes for the other. The train was too long for the station's high-level platform, and too long for a single side of the low-level platforms. Thus, the train used both sides of one of the low-level platforms. This resulted in two trains unloading simultaneously into the station using the pedestrian tunnel. The equipment from these two trains are used for the departing trains which were intended to be recorded, and as such passengers were not be able to board until the arrival, unloading, and cleaning of the late trains. A boarding call for both departing trains were announced ahead of the arrival of the late trains. The paths of passengers are illustrated in Figure 4.12 below. The paths of arriving passengers are shown in orange, and the waiting passengers for the departing trains are represented in green and blue respectively. Assuming that most passengers do not cross paths, the footage analyzed mainly captures passengers from the train which incurred the 50 minute delay.

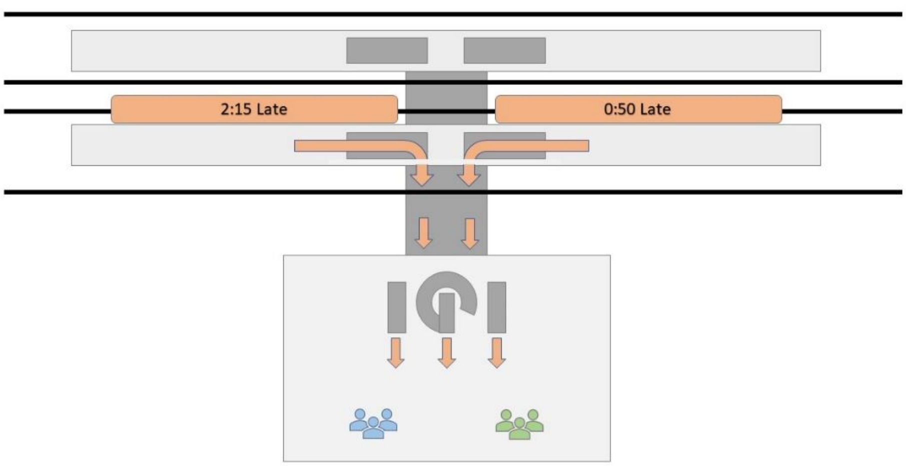

Figure 4.12: Arrival of joined late trains

Shortly after all passengers had disembarked from the trains and the trains were disconnected, the waiting passengers were directed to board, once again using the tunnel. This resulted in the simultaneous boarding of two trains using both escalators, the ramp, and the elevator. The paths are represented in green and blue as shown in Figure 4.13 below.

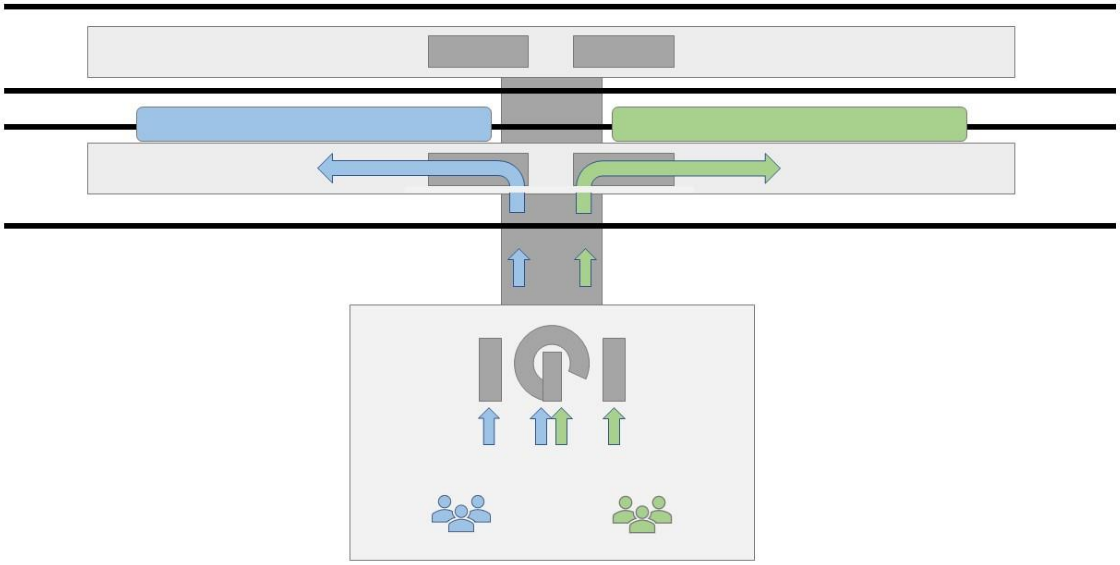

Figure 4.13: Boarding of late departing trains

As boarding progressed, a third train from the west arrived, approximately 30 minutes late. This added a third flow of passengers into the tunnel, where passengers disembarking from the recent arrival were walking against the flow of those who were still boarding. At this time, the escalator on the east side of the station malfunctioned, and boarding passengers were directed to the escalator on the west side of the station. Arriving passengers from the arriving train were all thus required to use the ramp. This resulted in up to two cross-flow situations and one counterflow situation. These are illustrated in Figure 4.14, below.

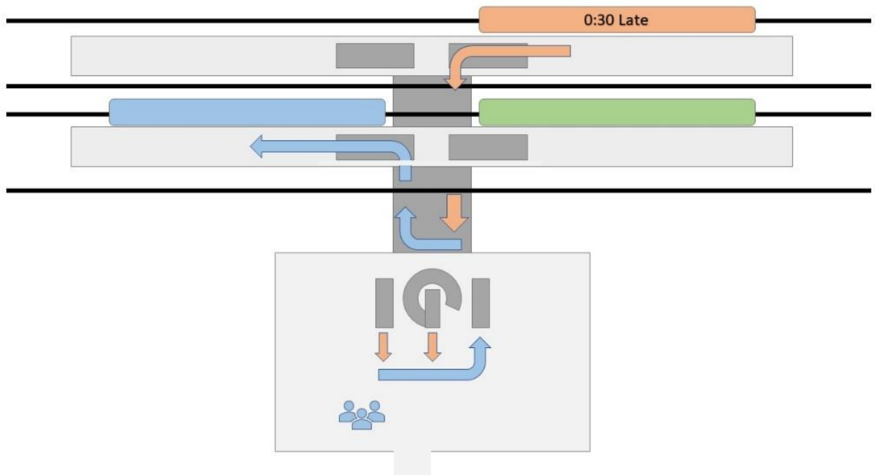

Figure 4.14: Boarding of remaining train and arrival of third train

The interactions between boarding and disembarking passengers resulted in a complex case which is difficult to predict and observe. As Semiautomated Tracking can generate movement speed data from partial journeys, it was possible to extract data from passengers in all of these stages after they had moved past the crossflow and congestion and were in relatively free-flowing space.

Despite the different delays incurred by passengers and the complex pedestrian trajectories, a large amount of detraining passengers were able to be tracked. The results and comparisons between the recordings are displayed below in Table 4.10, and a boxplot of each profile is also displayed in Figure 4.15. Note that the profiles are sorted by delay, not order of arrival.

Table 4.10: Arriving Passenger Profile Distributions

Time	*10 Mins Late*	*10 Mins Late*	*30 Mins Late*	*50 Mins Late*	*Overall*
Min	0.37	0.72	0.97	0.71	0.37
Max	1.57	1.88	1.66	1.91	1.91
Mean	1.11	1.16	1.28	1.18	1.17
Std	0.28	0.25	0.20	0.26	0.26
N =	57	62	28	47	194

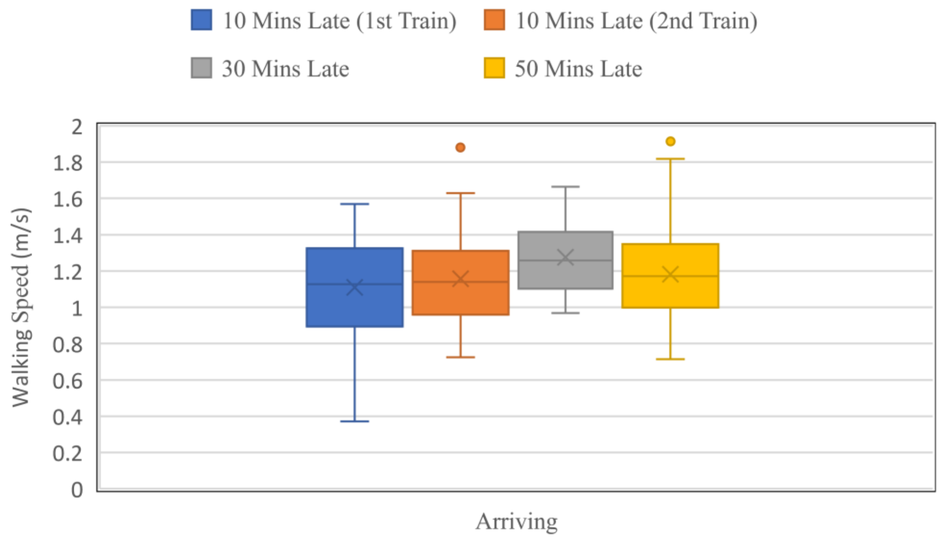

Figure 4.15: Arriving Passenger Movement Profile Boxplots

The mean for all 4 trials is somewhat similar, with a maximum difference of 0.17 m/s between a 10 minute late arrival and a 30 minute late arrival. This represents a 15% increase in walking speed, but the trend is not continued for the train which was delayed 50 minutes. In all cases, the mean walking speed is less than that of Network Rail's expected walking speed of 1.5 m/s for fit, healthy adults [6]. Unfortunately, it was not possible to determine the circumstances and/or reasoning behind the lower walking speed for the latest train, which arrived 50 minutes late. One potential reason could be the evening arrival, in which it is unlikely that passengers would have appointments to rush to following their arrival. However, this does not explain the faster walking speeds of passengers who arrived afterward on a train with lower delay. It also may be possible that these passengers had contacted any person or business that they were to meet, and thus rushing may be unnecessary. Further investigation is needed into why this may be the case, including the examination of late trains arriving in the morning or afternoon, and the arrival of early trains as well.

4.4.3 Accessibility

While analyzing the footage for both of the previous sections, additional tags were added as described in Section 4.3.3. to provide additional insight into accessibility for the diverse population which uses the station. While this is not a comprehensive overview of all passenger types, it does provide a quick look at some of the potential factors which may play a role in differing walking speeds. The results and comparisons between the recordings are displayed below in Table 4.11 , and a boxplot of each profile is also displayed in Figure 4.16.

Table 4.11: Accessibility Movement Profile Distributions

Tags	*No Factor*	*Suitcase*	*Phone*	*Family*	*Mobility Aid*	*Mobility Impairment*
Min	0.56	0.41	0.72	0.65	0.59	0.37
Max	3.73	2.45	1.47	1.82	0.80	0.67
Mean	1.18	1.08	1.08	1.07	0.69	0.52
Std	0.41	0.30	0.24	0.34	0.08	0.21
N =	163	162	20	16	6	2

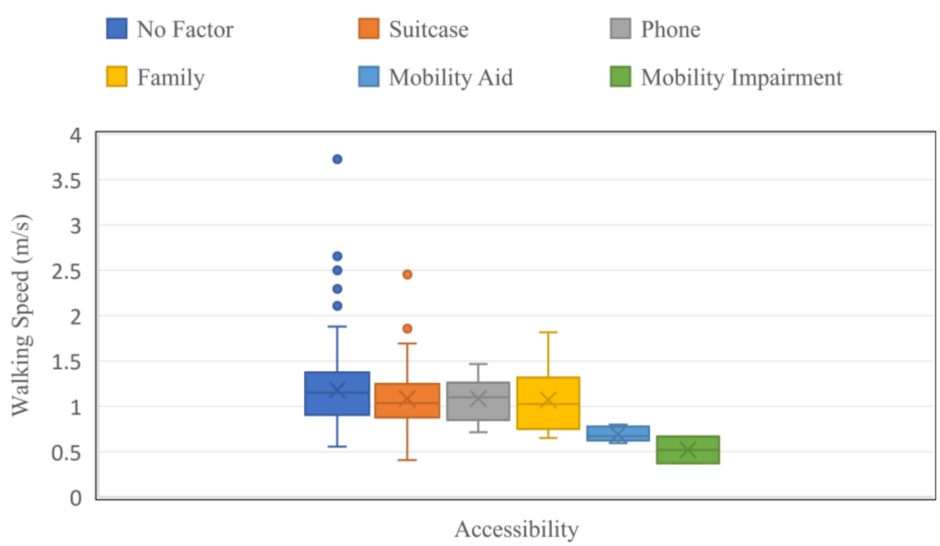

Figure 4.16: Accessibility Movement Profile Boxplot

From the above data, impacts and speed reductions can be seen for all examined factors. Passengers carrying a suitcase, using a phone, or travelling with children as part of a family all resulted in minor speed reductions of approximately 0.10 m/s compared to passengers with no factors applied. Suitcases were the most common factor observed, which is as expected for an intercity transportation terminal. Some occasional outliers exist from passengers running to the gate as described in Section 4.1.1. Phone users also had the same reduction in walking speed, but a lower standard deviation and a higher minimum walking speed. Families had the highest standard deviation, with some members moving quite quickly. It is noted that for both the phone and family profiles, the number of data points is low. This is significant, especially for families as they will naturally receive multiple tracks at similar speeds, thus contributing to a higher standard deviation. An example of this is shown below in Figure 4.17.

Figure 4.17: Family - Note family generates 1 track per member

Mobility aid users included those pushing luggage carts and wheelchairs. An example of a luggage cart is seen below in Figure 4.18.

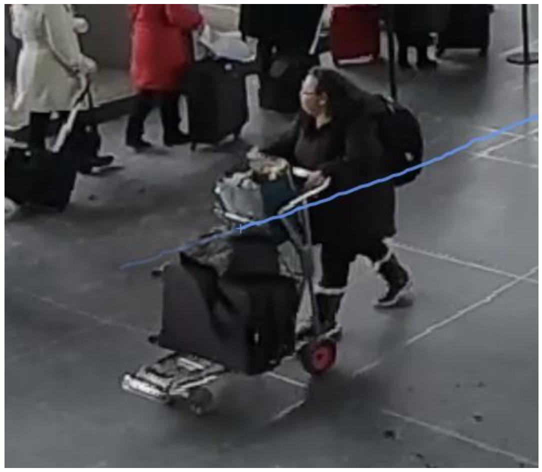

Figure 4.18: Mobility Aid User - Luggage Cart

Given the very small size of the station, the use of luggage carts is very low. Push Wheelchair users are also quite rare. However, their reported speeds are also well below that of the other profiles.

Mobility Impaired persons with crutches, canes, walking sticks etc. were even more rare, with only two persons analyzed. One of these passengers is shown below in Figure 4.19.

Figure 4.19: Mobility Impaired Passenger - Walking Stick

A large contributing factor may be from station procedures, where both of these types of station users would be invited to wait in a pre-boarding area closer to the gates and outside of Kinovea's analysis capabilities. Nonetheless, the reported walking speeds are significantly lower, well below Network Rail's and London Underground's guidance of 0.8 m/s., and also below that of NFPA's walking speeds of as discussed in Section 2.3. More investigation is needed in this area to increase the data and confirm the effects.

4.5 Discussion

4.5.1 Significance of Different Profiles

To determine the significance of the different profiles collected, the data from all 3 recordings was consolidated into a single database and analyzed in Minitab. A Two-Sample T-Test with a 95% Confidence Interval was run to compare the relevant data. Statistical Significance at a 95% confidence interval is achieved when the P-Value is less than 0.05. A 99% Confidence interval is suggested by previous work considering the potentially small differences in movement speeds [13]. This confidence interval is achieved when the P-Value is less than 0.01. Equal Variances were not assumed for this analysis, as some generated profiles had significantly different standard deviations. The results of the T-tests are displayed below in Table 4.12. The full Minitab outputs are also available in Appendix D.

Table 4.12: T-Test Results for Statistical Significance

Datasets Compared	*T-Value*	*Degrees of Freedom*	*P-Value*	*Significant Difference?*	
				95% Confidence	*99% Confidence*
10 Mins Late (1st Train), 10 Mins Late (2nd Train)	-0.95	113	0.344	No	No
10 Mins Late, 30 Mins Late	-3.16	51	0.003	Yes	Yes
10 Mins Late, 50 Mins Late	-1.06	85	0.294	No	No
Queueing, Late To Gate	-7.95	52	0.000	Yes	Yes
No Factors, Suitcase	2.38	294	0.018	Yes	No
No Factors, Phone	1.53	35	0.134	No	No
No Factors, Family	1.19	19	0.250	No	No
No Factors, Mobility Aid	10.55	18	0.000	Yes	Yes
No Factors, Mobility Impaired	4.34	1	0.144	No	No

The statistical analysis reveals significance for some profiles. There was no statistically significant difference found in the walking speeds from the first and second trains which both arrived approximately 10 minutes late. However, this was to be expected as there were no significant differences between them aside from the time of arrival. These two datasets were combined for later comparisons between 30 and 50 minute late trains. It was found that there was a statistically significant difference between passengers on the train that was 30 minutes late on arrival versus those which were closer to being on time, but not for passengers on the train which was 50 minutes late. This may indicate that once a train is sufficiently late, passengers will no longer feel the need rush to their destinations or onward travel connections.

A statistically significant difference was also found between the speeds of passengers joining a queue at boarding call versus those who arrive late to the boarding gate. This is as expected following the high-stress egress observations of the Stadium Rain Event. This is further corroborated by observations of passengers running or moving quickly as the departure time draws closer and the train departs. Therefore, the time-based stress state of passengers in the terminal may have an impact on walking speeds and movement profiles. This may lead to different results once incorporated into pedestrian microsimulation models.

While statistically significant differences were found for those with luggage and mobility aid users, other profiles such as phone users, travellers with children, and those with mobility impairments did not achieve statistical significance compared to the no-factor baseline. Additionally, statistical significance is only achieved with 95% confidence for those with luggage. This is largely because sample sizes remain extremely low, especially for these more specialized profiles. To resolve this, more data needs to be collected to increase the number of data points analyzed. Notably, the debatable significance of luggage on walking speeds is reflected in literature, with some studies finding no significance [35,36] and others showing speed differences [37].

All passengers were tracked and tagged for both urgency and accessibility simultaneously. As such, movement speeds of passengers in the accessibility profile will be affected by the urgency of their situation, and movement speeds of passengers in the different urgency profiles will be affected by differing levels of luggage, families travelling, and impaired passengers.

4.5.2 Benefits of Semiautomated Tracking

The analysis performed highlights many of the benefits of Semiautomated Tracking over manual and/or automatic tracking systems. While there are some advantages over automatic systems, most benefits are an improvement over manual tracking only. For example, the speed of tracking is significantly improved over manual tracking. In the previous undergraduate study of the station, each person had to be tracked across two different cameras and sometimes had travel times of up to a minute. With different potential trajectories, each person took approximately a minute to track, sometimes more. Furthermore, the footage constantly needed rewinding to return to the point at which the next person entered the station for analysis. For multiple-factor analysis of pedestrians in a wide corridor, specifically looking at accessibility, the time per person was estimated to be up to 8 minutes per person [13]. Semiautomated Tracking could be significantly faster, with 52 people tagged and tracked in less than 30 minutes during one instance. This was taken from a single camera with people spaced out to the point that multiple tracks could be generated simultaneously, as shown in Figure 4.20 below.

Figure 4.20: Multiple Tracking in progress

Even when not spaced out, the capability of using partial tracking and only analyzing a few seconds rather than the entire distance is highly beneficial. However, fully automated tracking systems may be capable of real-time data generation. It is noted that neither of these times include post-collection analysis. Profile Generator calculated the speeds and demographics profiles for all 356 tracks and 11 different profile types in under 7 minutes, averaging 1.17 seconds per track. This represents an analysis of 20390 lines of data for a rate of approximately 48 lines per second.

The number of lines calculated per profile depends on the number of frames of tracking. Under manual tracking, passengers must complete the entire trip from entry point to exit point (I.E. Gate to Main Entrance/Exit and vice versa) with no interruptions in order to be considered for tracking. In a railway station environment, this was observed to be difficult to find as many arriving passengers paused to adjust luggage and/or meet others, or took indirect routes to their exit. Boarding passengers had origins spaced throughout the waiting area and thus manual tracking was impossible. In other cases, even completed trajectories could be affected by including slower walking portions in higher congestion areas. As Microsimulation software uses freeflow speeds as the initial input, profiles affected by these factors cannot be used. Semiautomated Tracking resolves all of these issues by only requiring a few seconds of video to take as a measurement. Freeflow speeds can be generated from a portion of their trip which does not capture any impacts from pausing, indirect routing, or congestion. While this could also theoretically be applied to automated tracking, additional coding may be needed to differentiate freeflow conditions from those impacted by other factors.

Semiautomated Tracking also makes it possible to provide and evaluate multiple tags simultaneously. Up to 9 tags can be provided per track, and over 8000 different tags can be used to generate profiles on a single file. This allows for multiple types of analysis to be performed simultaneously in a single video playthrough. This is demonstrated in this thesis by analyzing both stress conditions and accessibility concerns. While this is also possible in manual tracking, data entry may be more difficult and each tag would require manual analysis and production of a profile. Fully automated tracking makes tagging difficult and time consuming if not impossible, especially when using non-video sensors such as LIDAR.

The use of videos also leaves the potential for higher detail analysis, and can provide additional unexpected insights that automatic tracking cannot. For example, several passengers were observed running to the gate not from the main entrance, but from the west side of the station. They were holding an item in their hand which could be a coffee or beverage cup. A new coffee and refreshments stand had recently opened on the west side of the station, which may have contributed to the late running of these passengers. This was outside of the original scope of the project, but may spur on additional focus and study. The ability to use videos also gives additional context to some actions, such as passengers leaving the gate and returning with luggage, or observing something such as a closing automatic door and running as a result. Finally, the use of videos means that the repurposing of pre-recorded footage is possible. In this case, video from a previous project was used, but this could easily be expanded to cover different past, present, and future scenarios.

4.5.3 Challenges and Limitations of Semiautomated Tracking

While the benefits of Semiautomated Tracking are significant, there are also challenges that should be considered, and resolved where possible. These range from simpler fixes such as the improper use of fisheye lenses, to unresolvable issues which must be kept in mind, such as the neglect of invisible disabilities. All of these may result in errors and inaccuracies in the data generated when compared to the real-world situation.

In this project, old footage was reused which was never intended for automated tracking. This led to several potential issues which should be kept in mind for future studies. The first challenge came from the use of fisheye lenses on all of the cameras. In uncorrected footage, this would have significantly distorted the video to the point that the distances would be inconsistent with the perspective grid, particularly at the edges. While correction factors were applied to the video, it was not possible to completely eliminate the effect. Nonetheless, the reduction is significant, as seen below in Figure 4.21.

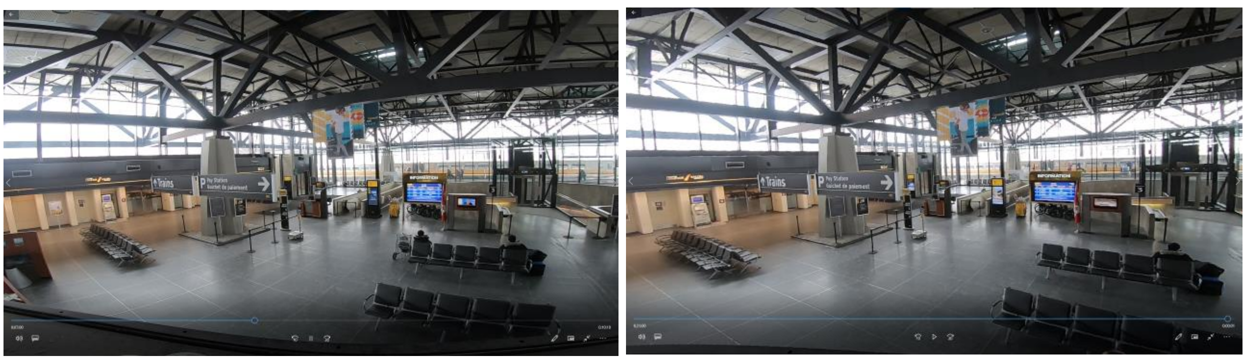

Figure 4.21: Footage before (Left) and after (Right) Lens Distortion Correction

As the effect could not be completely eliminated, tracking done at and near the edges may be faster than in reality as the track covers greater pixel distances, which translates to higher speeds when analyzed. In the future, the action cameras should be set to record in ‘Flat Projection’ mode, which eliminates the fisheye lens effect.

Next is the use of several different models of camera. At the time, the research camera fleet consisted of multiple different models of compact action cameras. While some efforts were made to keep the camera models consistent, there was no way to determine which model was used for each location. This complicated the removal of the fisheye lens effect as different camera models had differing levels of the effect. One camera is permanently fisheyed and should not be used in future collection.

The cameras used were placed on small compact tripods which were easily moved during the starting and stopping of filming, as well as battery replacements. As such, the calibration grid from one video was not able to be reused for other videos taken from the same perspective, as small differences in camera placement and angle caused grid misalignments. In the future, solid mounting brackets, remote start/stop for recording, and wired power could be used to minimize if not eliminate these misalignments.

While the camera challenges may be easily solved by changing the setup, there are also software-induced issues which may need further research, equipment, or programming to correct.

The need for a new calibration grid to be established each time also adds an additional layer of error, as the overall x-y grid used to generate the x-y data is extrapolated from the calibration grid's coordinates. These coordinates are user-set, and as such can be sensitive to error in placing the grid's points. Furthermore, some points may need to be estimated as the grid is raised to an estimated chest-height. As such, the point placement accuracy and therefore recorded distances may differ between different videos as well as between videos and real life. In the future, more research is needed to determine if a tool can be built and used to easily and consistently create these calibration grids.

Tracking also sometimes reveals a sinusoidal pattern which can be attributed to body sway. This is the natural left-right or up-down movement of a person's body as they walk. The effects can be seen in the wavy motion of the track in Figure 4.22, below.

Figure 4.22: Body Sway Impact on Trajectory

While generally minimal, body sway can add distance to the tracker which would result in faster reported walking speeds. A few solutions were found, including tracking hands pulling suitcases or pushing carts, as these wheeled objects were not subject to the swaying. However, one of the potential other solutions would be to constrain the speed measurement to only accommodate a single axis. This would successfully eliminate body sway, so long as the person walks straight along the measured axis. Furthermore, this technique could be used to measure body sway, which may be of interest for other studies. With additional programming, it may also be possible to constrain the speed to a straight line going from the track's origin to its final position.

Partially or fully occluded persons cannot be tracked easily using this technique, as the software requires a clear view of the object or surface being tracked. When occluded by other people or objects, the tracking is ineffective. While this does not necessarily pose a challenge for collecting unconstrained movement speeds, it does pose an issue for more congested environments. Camera angles may be useful for this, with top-down views being most effective at generating tracking speeds.

Backgrounds may also pose similar difficulties for tracking, as a combination of similar clothing and background colours can confuse the automatic tracking software resulting in mis-tracks which jump to other people or background objects. This was especially found to be an issue at night, as the recordings were taken in the winter and the darker coats and jackets blended with the darker posters and background of the station, as seen below in Figure 4.23, where a waiting passenger's coat is mistaken for the arriving passenger's backpack/torso. Note that these tracks can be recovered by removing the tracked frames prior to and during the mistrack.

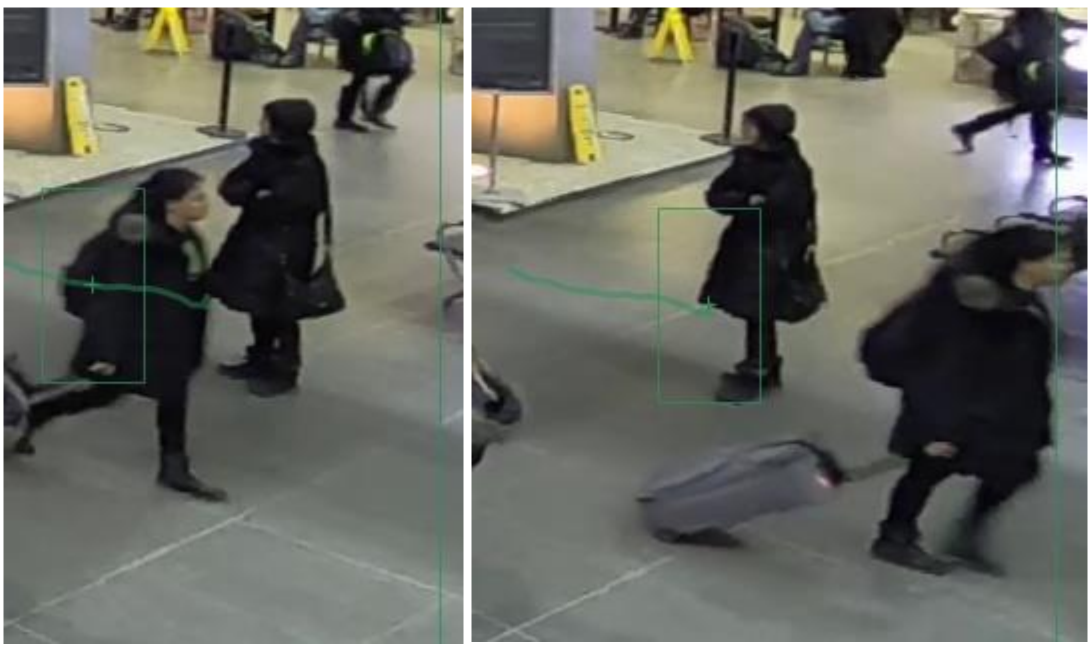

Figure 4.23: Mis-Track due to background similarity

Recordings should thus be taken during the day where possible, and in environments where clothing colours may be easily separated from the background.

There are some additional drawbacks to the methodology in general which should be considered. It is noted that these drawbacks also apply to both fully manual and fully automated tracking systems.

When generating the accessibility profiles, some of the counts are very low. However, this methodology can only analyze visible disabilities as it is video-based. However, there is a plethora of invisible disabilities which may be present in the data and not recorded as such. No additional information on the people is collected, and as such there is no way to determine the extent or effect of these invisible disabilities.

All of the data collection and tagging done is subjective, including the position of the tracking area and tags applied. As such additional biases may be introduced into the data. Where possible, multiple researchers should go through the same footage and compare the results generated to determine the variability and highlight any biases present. While this was not performed for this project, the high speed of data collection and generation makes this possible for future studies.

Perhaps the largest issue currently is that the methodology and software is not validated against true speeds, as there is no easy way to measure and determine these speeds with complete accuracy. Further testing is needed to determine an appropriate validation methodology and confirm that the speeds being generated by the software are correct and match real-world movement.

4.5.4 Future Applications and Potential

The future use cases for the methodology is quite vast, extending well beyond transportation terminals and video footage. Future work is required to modify Profile Generator to improve its capabilities and reach its full potential.

Profile Generator can easily be modified to work with other text-based input formats. In the future, more options should be developed to allow for x-y inputs from other video tracking software and hardware, including LIDAR and Stereo Cameras. This will allow Profile Generator to work with new potential video or data sources for further applications. Ultimately, any x-y coordinate source should be usable with Profile Generator.

In the far future, profile generator may be able to become more automated, with Machine Learning used to automatically apply tags based on video frames as needed for a fully automated solution. However, this will require significant advances in both development and technology.

For industry and engineering applications, the methodology has significant potential to improve data collection and allow practitioners to easily produce movement speeds for their pedestrian models or to meet client needs in observing occupant behaviours. The methodology is highly accessible, considering that Kinovea is open-source and Profile Generator is designed to run within Excel. Furthermore, the use of inexpensive cameras and potentially pre-existing CCTV systems minimizes equipment costs. Tracking and tagging processes within Kinovea are easy for new practitioners and requires little to no knowledge of computer vision algorithms and techniques. Profile Generator is almost completely automated, requiring only the selection of the output .txt file to run. This should allow practitioners to minimize training times and start using the methodology quickly. Finally, the time savings offered by Kinovea should minimize the number of working hours required to analyze acquired footage, reducing project costs or improving project results at minimal expense.

Ultimately, the use of Kinovea and Profile Generator may unlock a deeper level of analysis for security camera footage, provided that the camera quality is sufficient. This could spur on a new level of understanding for the field of pedestrian behaviour and microsimulation, as any building with a CCTV system could become an instant data collection site. Circulation within transportation facilities, shopping centres, stadiums, museums, and other buildings would become significantly easier to study without the need to set up additional equipment. However, the most significant use may be for fire safety, emergency, and other high-stress scenarios.

By having cameras at the right place at the right time, rare and useful observations can be captured. In the transportation terminal study, it was found that passengers in the high-stress situation of nearly missing their train resulted in faster walking speeds, in a situation induced by a snowstorm. This matches with the data from the Stadium study, in which a distinct difference between normal and high-stress egress was observed, including higher flow rates and faster overall egress times. However, both the snowstorm and rain event were rare and natural occurrences, not enacted by the researchers. With CCTV as a potential data source, the likelihood of having cameras at the right place and right time to capture rare scenarios such as fires, evacuations, and other emergencies increases significantly, enabling mass analysis of pedestrian behavior in a variety of situations across the globe. This is exemplified further by a co-authored research project and publication which used CCTV footage in a museum to examine behaviour in fire drills and unplanned evacuations [49]. The fulltext of this publication is provided in Appendix G.

Using the data from these scenarios can help engineers and practitioners get a better sense of how people behave and move under complex and rare conditions. This ultimately could translate into a better understanding of human behaviour in emergencies and further the development and validation of new pedestrian movement models.

4.6 Conclusions

In this chapter, the Semiautomated Tracking methodology was employed to analyze pedestrian walking speeds in a transportation terminal based on multiple factors. The factors for analysis were determined based on a previously conducted study of a stadium in which high-stress egresses were noted to differ from regular conditions. The analysis was conducted using videos adapted from a previous 2019 study of a Canadian transportation terminal.

The results of the analysis revealed that passengers who were arriving at the boarding gate close to the time of departure (I.E. High-Stress) moved 74% faster than those who walked to join a queue for boarding. The mean walking speeds for queueing and late passengers were 0.86 m/s and 1.5 m/s respectively. It is noted that the speeds of late passengers was more varied, with a maximum recorded speed of 3.73 m/s. While the means are within UK's Network Rail guidance, queuing passenger speeds fall on the significantly lower end of the proposed range, and the high-stress walking speeds match that of a 'Healthy Able-bodied adult'.

Passengers arriving on late trains had a minor increase in walking speeds for a train arriving 30 minutes late compared to other late trains arriving 10 minutes behind schedule. However, passengers on a 50 minute late train did not move much faster than those on a 10 minute late train. The overall mean walking speed for passengers, regardless of how late the arrival, was 1.17 m/s. This is less than Network Rail Guidance's for an elderly person's walking speed.

An examination of accessibility factors, including luggage, families, mobility devices and mobility impairments revealed differences from the mean walking speed of those with no tagged factors. The mean speed for those with no factors was 1.18 m/s. Passengers with luggage or phones saw minor speed reductions to a mean of 1.08 m/s each. Passengers using mobility devices such as strollers, wheelchairs, and luggage carts were observed to have larger speed reductions to 0.69 m/s, and passengers with mobility impairments such as canes, crutches, and walking sticks had the lowest walking speeds with a mean of 0.52 m/s. However, it must be noted that the sample sizes for some of these profiles are extremely small, especially for the mobility impaired and mobility device users. Unfortunately, the small sample size and relatively similar movement speeds pose challenges with statistical significance when using a statistical T-Test.

The use of Semiautomated Tracking to carry out the analysis demonstrates the benefits of the methodology. This includes the ability to quickly and easily generate movement speeds for more people thanks to the ability to use parts of a person's trip rather than the whole trip for data generation. When compared to automated systems, Semiautomated Tracking allows for a higher level of detail and analysis, revealing additional insights which would not be captured by fully automated methodologies. The ability to reuse and repurpose old footage also makes Semiautomated Tracking valuable for easily investigating pedestrian walking speeds from a variety of sources.

There are still challenges to overcome to make Automated Tracking more successful and useful. New tools and changes to camera setups can improve and simplify data collection. The methodology, much like others, cannot detect invisible disabilities, tagging is subjective, and occlusion remains an issue. Body Sway may add to the movement speeds generated, which may need to be accounted for or corrected. Most importantly, the methodology has not been validated against real-world movement speeds to determine accuracy. With more research, most of these challenges may be overcome.

This new methodology has the potential to improve the capabilities of video data analysis for pedestrian movement speeds and behaviour. With improvements and further testing, high quality CCTV and other video sources from anywhere in the world may be studied. This has the largest implications for fire safety engineering, where the use of CCTV footage would allow for analysis of real-world fires and evacuations after they have occurred, with no need for additional equipment setup.

Chapter 5: Conclusions and Recommendations

5.1 Summary

This project set out to determine if a combination of manual and automatic pedestrian tracking technologies could result in additional benefits over both, and apply the new methodology in a transportation terminal. This was inspired by a lack of local data for pedestrian movement speeds, including in Canadian transportation terminals. This is largely due to an overall difficulty in collecting this data, which is important for programming pedestrian microsimulation models which are used to design pedestrian spaces such as transit terminals. With easier data collection, pedestrian models can become more accurate and lead to better and safer design.

In Chapter 2, a literature review examined multiple topics around pedestrian movement data collection and transit terminal design. It was found that current models such as MassMotion provide default profiles which are based on circulation, but the use of local data may lead to more probable conclusions. Furthermore, the data currently in use may not reflect modern effects, and thus movement profiles may need to be updated. Some guidance regarding the input movement speeds for transit terminal pedestrian models was found for the UK, but no sources were found for Canadian transit stations. While technology and methods do exist for data collection, they tended to use specialized automated equipment or collected data in such a way that made it difficult if not impossible to discern between different populations using the station. Thus, a new methodology was needed.

In Chapter 3, Semiautomated Tracking was introduced as a newly developed methodology to respond to the needs established in Chapter 2. The methodology makes use of video footage processed in an object tracking software to generate x-y data which is manually tagged to add additional details and descriptions for later analysis. The tagged x-y data is then processed in a

VBA program to generate statistical distributions of each tag's data. A verification exercise used a video which was previously analyzed manually to compare the speeds generated with the new methodology. The new methodology was able to track and analyze most of the people, whereas the old manual method could only track less than half of the population to be analyzed. The speeds reported by Semiautomated Tracking were slightly higher than that of the manual method, but this could have potentially been due to errors in the manual method underreporting speeds. While a real-world validation was outside of the scope and capabilities of this project, it is recommended that this be done as soon as possible to increase confidence in the new methodology.

In Chapter 4, Semiautomated Tracking was applied to a set of videos taken from a previous study of a transportation terminal. The study was inspired by previous work done at a local stadium, in which a high-stress egress was observed to result in faster pre-movement times and higher flow rates. In the transportation terminal analysis, high-stress was deemed to be passengers arriving at departure gates shortly before the departure of their train versus passengers joining the boarding queue at the first call to do so. A secondary analysis on passengers arriving on trains with varying degrees of lateness was also considered. The need for accessibility data was also taken into account in the analysis, thus factors such as luggage, phone use, travelling with children, use of mobility devices, or having a visible mobility impairment were each considered. Thanks to the multi-tag capabilities of Semiautomated Tracking, these analyses could be carried out simultaneously. The results revealed significant differences in walking speeds for boarding passengers depending on whether they were late arriving at the departure gate, with late passengers moving an average of 74% faster. Passengers arriving on 30-minute late trains walked slightly faster, but there was no significant difference in the speeds of passengers arriving on very late trains compared to those which were more on-time. All accessibility factors appeared to have impacts on movement speed, with mobility devices and impairments resulting in the strongest speed reductions. However, the sample size for these profiles is very low. As such, statistical significance of the profiles was only found for users with luggage or mobility devices.

The use of the new methodology revealed several benefits including larger potential sample sizes, faster analysis, and higher detail. Challenges with the methodology were also revealed, including body sway and camera calibration issues. These challenges may be resolved in future work. Following improvements, Semiautomated Tracking may make it easier to collect data, especially from CCTV which can be particularly useful when analyzing rare situations such as emergencies.

5.2 Conclusions

The following key conclusions were drawn on the basis of the review, verification testing and experimental application regimes in this thesis, to determine whether the combination of automated and manual tracking can result in benefits.

- New and updated profiles with large amounts of detailed data are needed in order to improve pedestrian microsimulation modelling
- Modern data capture methodologies tend to use automatic tracking, which hides finer details and insights
- Open-Source object tracking software can be combined with other programs to be used for pedestrian tracking and pedestrian movement profile generation.
- Verification of Semiautomated Tracking reveals similar speeds, but different methodologies have different problems which induce their own errors.
- Validation for methodologies needs to be performed against truly known speeds.

- Semiautomated Tracking can reduce data analysis and movement profile generation times.
- Semiautomated Tracking can collect more data than manual tracking, as partial trajectories can be considered.
- Semiautomated Tracking can provide levels of detail in the analysis which are higher than automatic tracking.

Several additional conclusions can be drawn from the research and case study presented herein, including:

- Passengers who are late to catch their vehicle may move 74% faster than passengers joining a boarding queue at first call.
- The impact of late arriving trains is minimal for walking speeds, especially for very late trains
- Passengers with luggage or using cell phones may walk slower than those who do not.
- Passengers using mobility aids such as luggage carts or wheelchairs may move substantially slower than those who do not.

5.3 Design Recommendations

As a result of this project there are several recommendations, which are listed as follows:

- In the UK, Network Rail has established guidance for pedestrian modelling which can be used to evaluate the pedestrian circulation design of stations on the UK's national railway network. However, no guidance could be found for Canadian railway station design. A similar national standard guide may be useful to guide pedestrian circulation engineers in their creation of future pedestrian models.

However, this guide may need to consider different types of travellers, including commuters with higher familiarity with the station.

- Consider non-fire high-stress situations for egress and circulation. As demonstrated by the rain event, high pedestrian flow rates can be induced by other factors. In the case of transportation terminals, boarding passengers running late can move at faster speeds. This may also apply to different scenarios, such as transferring from one late vehicle to another, or in situations where stop dwell times are short.
- Consider movement speeds of those using mobility devices or those with mobility impairments when building pedestrian microsimulation models to determine additional travel time needed. This may also involve the use of other methods of vertical circulation or other needs.
- Consider security camera footage for potential human behaviour and motion data collection and analysis. The footage from these cameras may be useful for post-incident analysis of rare situations, which can further the understanding and design of pedestrian motion and spaces.

5.4 Research Recommendations

The following is a list of research recommendations which should be considered. Some of these are intended to be completed as part of future work in a PhD Project:

- Design and a validation exercise for pedestrian data collection methodologies which generates true walking speeds as a baseline for comparison.
- Apply the validation methodology to a variety of methodologies, including Manual, Stereo Camera, LIDAR, and Semiautomated Tracking to compare and contrast the benefits of each.

- Design new camera setups and apparatus for data collection to resolve fisheye lens, moving cameras and power source issues.
- Design new tool or method for easy creation of Calibration Grid
- Investigate effects of body sway on movement speeds, and potential for body sway studies using Semiautomated Tracking
- Investigate alternative technologies such as LIDAR, Thermal Cameras, or Stereo Cameras for use with Profile Generator
- Investigate additional needs for the use of CCTV video for use with Semiautomated Tracking
- Increase sample size of accessibility profiles such as phone users, travellers with children, or persons with mobility impairments. There may also be additional factors not considered herein.
- Investigate different user types and environments; intercity rail, commuter rail, metro, light rail, local/intercity bus, and aviation
- Investigate impact of concession stands and other station amenities on passenger walking speeds and circulation.
- Investigate factors which cause transportation terminal users to run, including visual, audio, and distance cues.
- Test high-stress profiles and conditions in pedestrian microsimulation software to evaluate the effects on final model results and station design.

5.5 Final Words

This thesis has revealed that aspects of automatic tracking software and manual notetaking can be effectively combined to analyze pedestrian movement speeds. Semiautomated Tracking is faster and potentially more accurate than manual tracking, while being cheaper and more detailed than fully automated tracking systems. The level of detail offered by Semiautomated Tracking has the potential to be a true springboard in pedestrian behaviour and motion research, as it can provide important context to the behaviours of pedestrians.

The capabilities of the methodology can be further expanded through the use of CCTV video, as this would effectively eliminate the data collection apparatus costs and efforts. Alternatively, the methodology could be combined with more automated tracking technology as it develops for faster high-volume speed generation while retaining the tagging capabilities. With the capability to collect data from a variety of locations, buildings, scenarios, and times comes the opportunity for increased understanding of pedestrian behaviour and movement. This can ultimately be applied to both circulation and evacuation scenarios, driving forward the next generation of pedestrian modelling and pedestrian modelling software.

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Appendix A: Variability in Stadia Evacuation under Normal, High-Motivation, and Emergency Egress

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Highlights:

- Stadium case studies displaying various levels of egress urgency are compared, including Normal, High-Motivation (Rain), and Emergency (Fire) Egress.
- Video footage of spectators is analyzed for selected contemporary behavioural theorems.
- Crowd density and movement speeds are compared between the levels of egress urgency.
- The role of staff in the evacuation process is found to be the predominant factor in reducing or extending premovement independent of the scenario.

Abstract

Egress modelling can be used in stadia design. This modelling describes the movement of pedestrians and crowd flow considering wayfinding and decision making in evacuation and circulation. The accuracy of the modelling is highly dependent on project-specific input data that accurately represents the movement of population with associated human factors considered. Currently, there are few contemporary studies of stadia that consider real egress decision making under a range of stimuli of which practitioners may use to influence their modelling and design process. Herein, a range of evacuation urgencies and their effect on pedestrian decision making and wayfinding in stadia are considered: standard post-game egress, egress under high-motivation conditions, and emergency egress. This is done through carefully collected and recorded observation of real stadia in Canada and obtained third party video for stadiums internationally.

To reinforce findings, real case studies of other notable emergencies are also considered. Decision making at all stages of evacuation are analyzed. Results indicate that, based on the cases examined, the egress behaviours differ in relation to the level of urgency, such as high motivation and emergency, and gate densities are higher for high motivation egress by a factor of 1.5. The role of staff in the evacuation process is one of the predominant factors in reducing or extending premovement regardless of the scenario. Associated contemporary behavioural theorems are used to explain differences in movement and decision-making in evacuation scenarios.

Keywords:

Human factors; response patterns; egress; hazard evaluation; decision making;

A.1 Introduction & Motivation

Accurately representing pedestrian behaviour and movement is of critical importance in the design process of stadia, particularly in the case of emergency evacuations (fire, terrorism, etc.). To accurately create an evacuation model of an emergency egress, the complex field of human behaviour must be incorporated. Currently, there are few documented studies where stadia movement is quantified that may be used for validation modelling to assist design. Additionally, the current understanding of human behaviour in terms of decision making and way finding is lacking. This can limit resulting model configurations with uncertainties, biases, assumptions and generalizations. The research herein is a continuation of previous studies which considered the quantification of movement speeds for modelling egresses of Canadian stadia [1].

The purpose of this first-stage study is to determine and reveal differences in egress behaviours under various circumstances to aid in producing refined modelling inputs and parameters for future validation and verification of stadia. While movement speed data is critical in the modelling process, this has been addressed elsewhere and is not the current paper’s focus.

Instead, this paper focuses on the various behavioural factors to be considered during a stadia evacuation. The scenarios herein include a normal egress (post game), a high motivation (rain downpour) evacuation, and an emergency (fire) induced evacuation in Canadian stadia. Two additional emergency evacuation case studies of stadia (one historical and one contemporary) were considered to confirm the behavioural actions observed in the emergency scenario.

The combined results of the studies in this paper go beyond congestion and movement speed analysis to compare and highlight the differences in the behaviour of stadium spectators under different situational parameters, using the modern behavioural theories. The focus of this study places emphasis on emergency evacuations, investigating how the type of stimuli and threat perception may affect a person's response to the cues to leave and their behaviour in the process of evacuation afterwards [2]. This study also aims to highlight the significance of the role of staff and authority on the stadium evacuation process. The behaviours observed herein are explained through behavioural and decision-making models. Although limited theories were used, we acknowledge that additional behavioural frameworks could also be considered in future analyses to build upon this foundational research. Due to the rarity of real urgent and emergency egresses, only one trial for each scenario was recorded and analyzed. The authors acknowledge that the information collected for this study is limited and more data is needed to confirm the behaviours and effects observed. Although limited to the specific scenarios and locations considered, this study suggests potential useful considerations when tailoring future evacuation models that incorporate more defined behavioural actions and for the management of stadium evacuation.

A.2 Background

Stadia design presents unique challenges to accommodate not only large crowd sizes, but full evacuations of these crowds during regular egress and high motivation and emergency scenarios. From 1961-1971, multiple incidents resulting in pedestrian injury recurred at Ibrox Park in Glasgow due to unsafe measures in a stairwell, contributing to 68 casualties and 219 injuries total. These events led to a report by Scientific Control Systems (Commonly referred to as the SCICON report) [3] and subsequent Green Guide documents which revolutionized stadia design in the years that followed. Examination of stadium disaster case studies from 1981 to 2017 (see Table A.1) illustrate that stadia still require additional research and standard development that involve an understanding of associated human factors to minimize injury during evacuation. The various range of stadia incidents demonstrate the large role of pedestrian motion for the range of scenarios of emergencies, as most disasters were due to crowd movement. The purpose of the table is to define the scenarios and country to consider cultural effects and scenario-specific data. Details of the involved pedestrians and population in attendance has not been provided as the data is unreliable.

Table A.1: Selected Stadium Incidents

Year	*Stadium*	*Country*	*Capacity*	*Disaster*	*Casualties*	*Injuries*
1981	Karaiskakis Stadium	Greece	32,115	Crowd Crush	24	N/A
1982	Estadio Olimpico	Colombia	72,698	Crowd Crush	21	55
1982	Luzhniki Stadium	Russia	81,000	Crowd Crush	66	61
1985	King Baudouin Stadium	Belgium	50,093	Riot	39	600
1985	Bradford Stadium	England	25,136	Fire	52	265
1987	Tripoli International Stadium	Libya	65,000	Structural	20	N/A
1988	Dasarath Rangasala Stadium	Nepal	15,992	Crowd Crush	93	100
1989	Hillsborough Stadium	England	39,732	Crowd Crush	96	766
1991	Oppenheimer Stadium	South Africa	23,000	Crowd Crush	71	N/A
1992	Armand Cesari Stadium	France	16,078	Structural	18	N/A
1996	Independence Stadium	Zambia	30,000	Crowd Crush	9	78

1996	Tripoli International Stadium	Libya	65,000	Riot	50	N/A
1996	Mateo Flores National Stadium	Guatemala	26,000	Crowd Crush	80	147
2000	Samuel Kanyon Doe Sports Complex	Liberia	50,000	Crowd Crush	3	N/A
2000	Harare Stadium	Zimbawe	80,000	Crowd Crush	13	N/A
2001	Stade TP Mazembe	Congo	18,500	Crowd Crush	8	N/A
2001	Vatani Stadium	Iran	15,000	Structural	3	N/A
2001	Accra Sports' Stadium	Ghana	40,000	Riot, Crowd Crush	126	N/A
2001	Ellis Park Stadium	South Africa	62,567	Crowd Crush	43	51
2009	Le Felicia	Ivory Coast	50,000	Crowd Crush	22	N/A
2012	Port Said Stadium	Egypt	18,000	Riot	74	1000
2013	Le Felicia	Ivory Coast	50,000	Crowd Crush	61	200
2017	Manchester Arena	England	14,200	Terrorism	22	800

A.2.1 Crowd Flow Considerations in Design

Crowd management was examined significantly in 1972 by SCICON [3], with the aim of "*developing [a] method of assessment for establishing the design characteristics for safe movement, accommodation and control within football stadium and its immediate environment*" [3]. Through a series of stadium studies in the UK, those authors described that when evacuations surpass 7-minutes, crowd pressure becomes severe, flow becomes turbulent, and evacuees display visible signs of anxiety. As a result, those authors believed that after 7 minutes, individuals may lose control over their own movement. These findings are what formularized as the 8-minute rule [4] and has since been used as the criterion basis for calculating capacities of exit routes in many global jurisdictions. Two later studies performed on Canadian stadia in 1977 [5] and 1982 [6] with evacuation times greater than 8 minutes found inconsistencies with this guideline. These studies raised important arguments suggesting that the accepted egress estimates for crowd flow were unrealistic and standards of safety were not explicitly established nor well understood.

It is also important to remark that many of the studies that followed in North America influenced different prescriptive requirements. In North America, the National Fire Protection Association (NFPA) 101 Life Safety Code is used to determine egress standards for stadia [7]. Stadiums designed under NFPA 101 must conform to maximum permitted travel distances to exits, which limits the stadium's overall evacuation time. Similar to SCICON's 8-minute rule, NFPA 101 also has regulations requiring that the design will allow people to egress from the stands to reach an egress concourse within a nominal flow time. However, instead of a single value, NFPA 101 uses a linear relationship to determine the nominal flow time based on the number of seats. This ranges from 3.3 minutes for a 2000 seat stadium up to a maximum of 11 minutes for a 25000+ seat stadium. This nominal flow time refers to the minimum flow time for the most able population; some less able spectators or spectators unfamiliar with the environment may take longer. Because these approaches were based on studies that were completed prior to the development of computational tools, they lack quantitative results required for modern modelling applications, as well as available raw data to further advance theories of the associated human behaviour.

A.2.2 Consideration of Human Behaviour in Pedestrian Modelling

A review study by Meacham in 1999 [8] found that the initial prescriptive-based regulations have led fire safety engineers to potentially be unaccustomed to fully considering human behaviour and response factors within evacuations. With the transition towards performance-based design, an increased understanding of human behaviour and response issues are needed for fire safety management plans. It should be considered that delays are inherent in human response to an emergency, which translates to delays prior to evacuation commencement, delays during evacuation and the potential for some people to not evacuate on their own. Meachan also suggested that modelling must work towards incorporating a more thorough understanding of human behaviour [8]. Harney [9] follows by providing a more in-depth review of crowd modelling approaches. Harney's analysis of agent-based modelling as an emerging technology proved it to be a promising approach that can aid in providing realistic microscopic analyses. Here, agents possess intelligence and adaptability and thus have the ability to pursue independent action and interact with other agents. In the study, a variety of approaches are compared to understand what methods are successful and accurate. These approaches include a multitude of both microscopic models, in which the data focuses specifically on individual pedestrians, and macroscopic perspectives. In this, the crowd is looked at as a system rather than individual agents. Harney concludes that the models can be applied to large-scale problems [9]. However, their effectiveness is reliant upon available movement data and well-developed theories to predict the way people move, either as part of a software's inherent algorithm or through user inputs. Harney notes that because pedestrians are constantly interacting with their environment and others changing their movement accordingly, it is more difficult to capture data which encompasses their behaviour. The limited availability of movement information within detailed scenarios emphasizes the need for egress studies to provide validation for simulation models, since the reliability of these egress models in performance-based stadium design is dependent on the confidence of the input data.

There are several potential empirical methods for examining crowd behaviour and motion, as summarized by Haghani and Sarvi in 2018 [10]. The methods summarized exist on a continuum between laboratory and field in nature. More lab experiments may involve human or animal subjects in controlled lab environments, VR, or hypothetical-choice scenarios. Other methods such as analysis of natural walking, and analysis of natural disasters are more on the field end of the spectrum. Evacuation drills and post-disaster interviews are in the middle of this spectrum. Lab studies were found to have more control over variation and responses, and as such were more replicable. However, these studies lacked contextual realism and environmental realism. As the studies become more field-like in nature, they become more realistic with observed decisions and behaviours made in response to real-life situations within a more natural environment. However, this removes significant amounts of control over variation and responses. As such, these studies are harder to replicate, with a potentially low number of possible repetitions.

Fire drills are shown by Haghani and Sarvi to be a middle ground, with moderate levels of environmental realism and replicability. However, they also have their drawbacks as well. Gwynne et. al. [11] examined the strengths and limitations of fire drills relative to other egress methods for assessing evacuation performance. One of the key challenges with the use of drills is that inducing additional factors to drills representing more restrictive or urgent scenarios may expose evacuees to potential injury, stress, anxiety, and potentially crush situations. As such, these more urgent factors cannot be added to drills despite adding to the realism and credibility of conditions faced. Another challenge is that it may be difficult to place instruments within the building to collect sufficient data without influencing the outcome from occupants seeing the cameras and staff. Alternative methods for determining egress training and assessment are also compared, including use of simulation tools, lab experiments, and VR. Many techniques such as information sessions, post-evacuation debriefing, and mental rehearsals are more aimed at training and evaluating egress outside of actual drill/emergency environments and are proposed as complimentary tools for measuring the effectiveness of evacuations.

Each method has its own merits and drawbacks, but for maximum realism and examination of realistic environmental effects, field analysis of behaviour is needed. It should be noted that these studies are thus less replicable and harder to extract data from, especially when analyzing motion or movement speeds.

Considering the challenges of field analysis, knowledge and understanding regarding how people move and anthropometric data is currently limited. Fruin profiles of movement [12], for example, are presented independently of the demographic for which they were derived from. This method applies a nominal distribution of a single walker speed from a general circulation study to represent movement, which is used to randomly assign a speed for all agents [12]. Careful examination of different studies reveals that movement profiles can be approximations of the overall population and are loosely based on the collected movement and behaviour data. The Ando movement profile [13] is an example of this. When translating this highly cited paper, it was found that explanation regarding methodology and collection methods of the movement data lacks details [13]. Similar issues are present with the studies performed by Pauls [5, 6, 14]. Pauls' studies would appear to be particularly interesting in relation to this study as they are also performed at Canadian stadia like those of the authors. However, those studies predate the widespread use of computer-based pedestrian modelling and digitized data collection, and thus the final findings lack the necessary detail for modelling software input parameters.

More recently, the authors have begun to compile input data pertaining to movement speeds and anthropometry. While these have been preliminarily introduced elsewhere by the authors in another publication [15], that study's scope did not detail the human factors or decision making that influences egress. A recent study by Larsson et al. [16] was conducted to update movement statistics with contemporary data. Those authors produced quantitative data on the relationships between crowd flow, density, and velocity for the following four events at a multi-use stadium in England: football, rugby, a male music performer, and a female music performer. Density was demonstrated to be inversely related to the velocity and flow. As well, the density of the crowd will often be the dictating factor of the velocity and flow. For example, a decrease in density will increase flow and velocity as the crowd can move more easily. On the contrary, an increase in density will decrease the flow and velocity. The study then produced population densities, flowrates and velocities which had all fell below those typically assumed by the Green Guide [4], thus confirming the need to continually update engineering tools (data and methods) with contemporary results, and further analyze the underlying factors that define these results. Through the comparison of the four events, the authors were able to qualitatively attribute limited factors to the observed variances in crowd flow, density, and velocity. The interactions within the crowd were believed to be affected by the following physical and social parameters of the different demographics: population density, body footprints, walking speeds, group size and cohesion, and other situational parameters (e.g. time of day, time of year, and whether the team won or lost) [16]. That analysis, however, did not consider human factors or external stimuli to evacuation, and instead called for continued studies to give more detailed attention to the underlying conditions that can explain the differences between demographic compositions, group behaviours and the resulting impact on egress.

A.2.3 Contemporary Behavioural Frameworks

Haghani and Sarvi [10] also indicate that accurate and reliable models need to accommodate psychological and behavioural phenomena, which they categorized as strategic-level ("What-to-do"), tactical-level ("Where-to-go"), and operational-level ("How-to-get-there"). They also indicate potential topics for further research including roles of stress and time pressure on egress decision-making, considering the nature of individual differences in perception and responses.

Decisional frameworks such as the Protective Action Decision Model (PADM) [17, 18] could be considered to examine decision making stages in emergency egress situations. This model is based on the research of people's responses to environmental hazards and disasters – it attempts to describe the pre-decisional and decisional sequence of action making. The PADM framework, however, remains a hypothetical provisional framework that is yet to be validated with application to emergency-based evacuation scenarios. A review study by Kuligowski in 2013 [19] analyzed the present methods to attempt to incorporate occupant behaviour in modelling with simplified behavioural processes. It was found that users could assign periods of delay to occupants to represent pre-evacuation period, and sequences of actions to simulate interruptions to continuous movement. These approaches, however, rely on the user's inputs in which there is limited available guidance, comprehensive dataset, and behaviour theories to reliably predict behaviour [19].

To promote the consideration of behavioural components in evacuee modelling, emerging studies have compiled a set of behavioral statements of key behaviors that people exhibit during an evacuation [20]. Other studies have highlighted that such decision making within the evacuation process can be suboptimal and/or result in mistakes being made caused by cognitive biases [21, 22]. In these studies and video analyses, it is important that caution be undertaken to reduce the subjectivity of looking for specific actions, where new actions may also be observed. It is acknowledged by the authors herein that there are multiple behavioural frameworks (with some emerging such as social identities for example [23]) that could be considered to describe egress. To further explore the egress process herein, we have focused our attention to behavioural heuristics such as cognitive biases. Biases have the potential to affect a person's decision-making process, primarily by delaying/ or hurrying the decision to evacuate. However, to truly validate their presence and significance, surveys with those who egressed are needed, otherwise definition is too subjective. In that sense, the behaviours classified herein will not encompass all possible occurrences.

A.3 Methodology

The following tables describe information of the events which were investigated by the authors. Table A.2 lists the primary studies of this paper. Table A.3 lists the supporting studies that are later used to interrogate observations. Further details on the stadia, events, methods of data collection and analysis, and conditions of egress are outlined within the subsequent sections. All studies were analyzed individually by three members of the authors' research team and results later compared to reduce subjectivity of visual observations. The footage from these videos allowed for the generation of a timeline to determine and reveal key events during each egress and quantify re-occurring behaviours. The timelines listing observed patron behaviours are a compilation of observations by the authors, most of which were verified to be the same across all three researchers with the exception of a few people for individual behaviours. Where a disagreement or ambiguity existed, the footage was reviewed by the three researchers to confirm or reject the observation. Flow counts were also performed at the exits by counting the number of patrons passing through at approximately 5-second intervals and were added into the timeline after the flows were determined. This was the same procedure used to count exit use proportions for way-finding.

Similar protocols to the rain and standard egress scenarios were used to generate the observations for the fire scenarios. However, no flow data was collected due to the inconsistent camera angles and footage.

Table A.2: Egress Scenarios Collected and Studied by the Authors

Event	*Filming Date*	*Attendance who egressed*	*Egress Type*
Tennis Stadium	2019	12,000	Normal (Post-Game)
Tennis Stadium	2019	2,000	High-Motivation (Rainfall)
Football Stadium	2018	128 (one stand)	Emergency (Fire)

Table A.3: Comparative Events Considered from Existing Literature

Stadium	*Location*	*Date*	*Event*	*Attendance*	*Egress Type*
Nissan Stadium	Nashville, USA	September 15, 2019	National Football	62,849	Emergency (Fire)
Bradford Stadium	Bradford, UK	May 11, 1985	English League Football	11,076	Emergency (Fire)

A.3.1 Tennis Stadium – Standard and High-Motivation (Rain) Egress

This stadium is a fifteen-acre multipurpose sport and entertainment complex integrated into York University in Toronto, Ontario. It regularly hosts professional tennis tournaments each summer. According to CAD floorplans of the stadium, each gate is 2.54 meters wide at its entrance, which is the narrowest point, and the walkways leading to these exits are each 2.89 meters wide. As the stadium is highly symmetric, these measurements are the same for all 8 gates and the perimeter walkways leading to them. These CAD plans have been reproduced in a simplified manner and are provided with the pertinent dimensions below in Figure A.1. A seven-day event was selected to conduct multiple data collection studies, some of which are beyond the current scope of this paper (movement speeds for example). Filming required the rotation of six researchers of the York University Fire research group. Stadium film access was granted by the university, and spectators were informed of filming and photography taking place. The methodology and data collection procedure had been inspired by methodologies described by Pauls et al. [14]. For the focus of this study, the authors set-up equipment to record and analyze human behaviour in the main stadium. During this tournament, spectator access to the upper deck was not permitted, allowing for the research team to set-up unimpeded panoramic views of the stadium bowl and grounds. A series of GoPro 7s (1080p HD resolution) were stationed at two carefully selected vantage points, as displayed in Figure A.2 with their respective fields of view. Figure A.3 shows a sample still photo taken from the video footage. Both Standard and High Motivation egress events used the same filming methodologies.

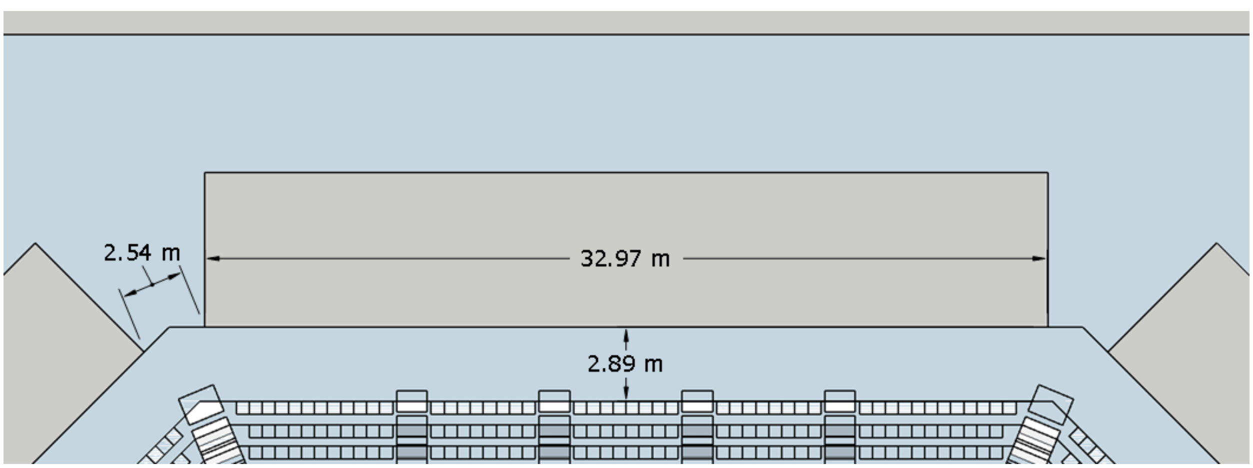

Figure A.1: Dimensions of walkways and gates, taken from proprietary CAD drawings of York University Stadium

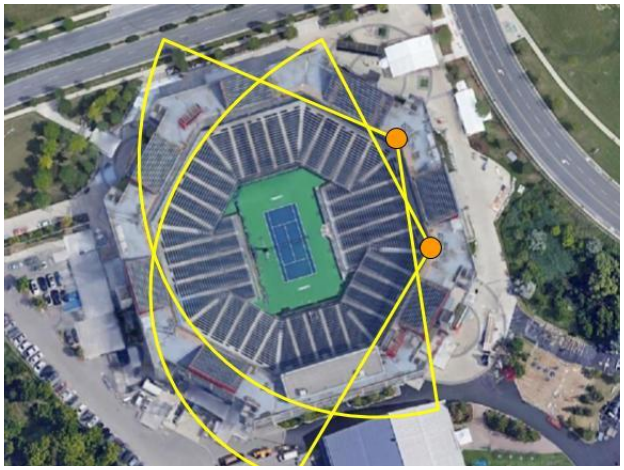

Figure A.2: Tennis Stadium at York University camera stations and approximate field of view.

Figure A.3: Still image of a utilized Centre Court camera illustrating an observed gate.

Filming was continuous from opening of the stadium to the second to last match. The highest attended match would be the second last every night and this was predominately at full capacity. The attendance rate of the unfilmed last match of the night would often be about 20% capacity.

With the objective of capturing an emergency egress, artificially induced events such as fire drills were prohibited from an ethical and scheduling standpoint by the university. However, for high motivation egress filming, the authors considered adverse weather conditions as the stadium is open to elements with no overhead shelter with exception of the stadium concourse. The authors therefore had to time filming with a sporting match in progress and a downpour of rain significant enough to end the match. It was critical that rain occurred suddenly, as the match would then be suspended, and a full evacuation of the stadium bowl would then take part as there is no shelter from rain. Sudden rain events in tennis suspend play, whereas periodic rain will not suspend play. The procedure when play is suspended is to evacuate the stadium bowl and the spectators can then take shelter. It should be noted that not all sports will follow this procedure; in Canadian football for example, play will not stop when rain occurs and is continuous.

Filming was continuous for the duration of the seven-day tournament, in which one rainfall event was observed. The authors recorded an afternoon rainfall event and observed an egress of approximately 2000 spectators for that event (this is an expected attendance that is often seen in afternoon matches). No other rain events occurred in that tournament. The entire stadium was recorded with two gates filmed at close range. This permitted further observations to compare to other scenarios and stress states, and congestion. It was not possible to survey the spectators of the stadium afterwards as this was beyond the ethical clearance granted to the authors. Therefore, the authors are reserved in quantifying specific types of behaviours where subjectivity is present.

In both scenarios, Gates B and C (at the location of cameras A and B, respectively) were used to record the amount of people arriving at and departing from the gate every five seconds during the egress. The data from the camera footage was then used to develop graphical interpretations of the egress: the percent of the population egressed with time, and the flow of people per unit width of the gate with time. Additionally, records were taken to track exit usage by assigning the chosen exit to each spectator. These results are coupled with qualitative interpretations and behaviour descriptors as discussed in Section 4.1.

A.3.2 Canadian Football Stadium – Emergency (Fire) Egress

The fire egress study was taken as a case study regarding the behavioural aspects of stadium spectators during an emergency. This case study reviews the event of a localized fire at a Canadian Football stadium (the same as noted in [1] but recorded by third party spectators). The stadium itself did not have available footage of the event, nor did the authors have high-resolution cameras permanently installed on-site (the authors research team has had ongoing filming studies here since 2017). Therefore, this study is limited to footage recorded (7 short films) and shared by spectators to the authors. The vast majority of fans were in the south stands, with some fans of the opposing team in the lowest section of the north stands, highlighted in the figure below. There were no people in the upper section of the north stands. The focus of the behavioural study herein was on the localized stand area (refer to Figure A.4) as clear footage for the adjacent stands was not publicly available.

Figure A.4: Canadian Football Stadium aerial view (incident stand highlighted) (left) and still image of publicly posted footage captured by spectators at the event (right)

A few fans of the opposing team lit flares and other incendiary devices, which resulted in a small explosion and set their banner on fire. The incident occurred in the second half of the match, and the opposing team was winning by one point when the fire occurred. The fans who were actively involved in the lighting of flares were identified as 'masked individuals' as they were seen wearing masks during the incident. At the beginning of the footage, the stands where the fire took place was at approximately 20% of the capacity, with 32 people present. The adjacent stand was considered to be at capacity, whereas there were no spectators present north of the considered area. The seats in these stands are typically sold to encourage spectators who support the opposing team o sit together. The authors acknowledge that this study is limited to footage obtained from publicly supplied video, and therefore there is a gap in the pre-evacuation behavioural observations of all spectators. The reported quantifications herein are noted as estimations because the smoke and camera quality impair the visibility. The videos were time-matched by the authors based on key events to create a global timeline of the fire and observed behaviours (see Section 4.2).

A.3.3 Study Limitations

There are inherent limitations in this study due to the low number of locations studied and the low number of scenarios observed. While circulation (i.e. regular post-game egress) is extremely common and collecting footage is therefore easier, higher-motivation egresses such as the rain scenario and fire scenario herein are considerably rarer and therefore much harder to capture. It is rare to get multiple instances of genuine rain or fire evacuations at the same venue, let alone capture that data for analysis. Thus, the available dataset is limited to the three scenarios described herein, with one trial for each scenario. As such, the conclusions of this study are limited to the specific scenarios discussed. Each scenario has a different distinct cause and conditions for egress, leading to different results. These results do not imply that an egress under these conditions (Normal, Rainfall, Fire) will always have the same effects, as behaviour may be influenced by additional unspecified factors such as architecture, demographics, venue, etc. Counter-flow was observed, particularly under normal conditions, which could also impact the flow of patrons in an inconsistent manner. The fire scenario observed has a particularly low occupancy, and footage was captured by several bystanders and TV broadcasters, instead of from researcher-controlled cameras. The behaviours observed were compared however with other similar stadium fires, as seen in sections 4.2.2 and 4.2.3, to expand on the available data. This study is first stage and designed to be built upon with additional data and analysis considering more of these rare events and their distinct conditions.

A.4 Behavioural Observations

A.4.1 Standard Post-Game and High-Motivation (Rainfall) Egress Studies

The standard post-game egress at the Tennis Stadium was analyzed in over 13 minutes of video footage. It is important to note that the video was recorded at the end of the second to last match so egress would be influenced by crossflow from other entering spectators. Table A.4 lists the timeline and observed behaviours that influenced egress. The origin (00:00 time) is when the match had ended. The overall egress of the stadium from this match was approximately 13 minutes with no observed signs of excess congestion or competitive behaviour.

Table A.4: Decisional Behaviours of the Standard (Post-Game) Egress

Time in videos (m:ss)	*Decisional Behaviours and Key Events Observed*
0:00-0:30	• Even though the match has ended and employees have opened aisle barriers, there are still spectators watching the court players. Main egress begins where spectators predominately exit the gate they entered. • At approximately 15 seconds 8% of the population is in movement, by 30 seconds this is 14%.
0:30-0:48	• Spectators begin egressing but some stop mid stairs to look at the court activities (1.5% of total population). These spectators loiter at the perimeter of the bowl again watching the court activities. Stairs begin to show congestion with starting and stopping of spectators.
0:48-0:58	• As this match has ended, a new match will begin in about half an hour, evidence of cross flow occurring with people entering.
0:58-1:48	• Players exit the court and applause stops, egress increases
1:48-3:48	• An interview begins of winning player shown on stadium screen, similarly before egressing people stop and watch the screen periodically. Some have not left their seats.

3:48-4:35	• Once interview ends, egresses pick up. This is the last game related activity. Peak flow occurs at 89 Ped/min/m width.
4:35-7:06	• After peak flow, egress subsides. Announcer comes back on to announce winner and waive of prizes. This again results in a distraction of people leaving the stadium (loiter in the bowl and on the stairs), where 1.8% of the total population per stand some turn back. • Only 7% of those in attendance remain sitting and not in the process of moving by 4:35.
7:06-8:24	• Final acknowledgements by announcer.
8:24-13:05	• Gate usage is steadily decreasing from 20 Ped/min/m to minimal.

For the rain evacuation at the Tennis Stadium, the total recorded egress was 2 minutes 55 seconds. Table A.5 displays the timeline and observed behaviours which appeared to influence egress. The origin (00:00 time) is taken as just a few seconds before a formal announcement is made, because at this time, some spectators had already begun evacuating. It is here that some of the same behaviours observed in the fire event (next section) are revealed. Normalcy was quickly subverted, as the game was immediately stopped, a clear deviation from normal gameplay. Potential Authority actions and influences were observed, with the entirety of the stadium standing to egress within seconds after the Chair Umpire, who prominently holds the highest form of authority for players during the match [24] and is heard by all audience members, announced suspension of play. The authority exhibited here may be similar to the Beverly Hills Supper Club Fire, where a busboy interrupted a performance to advise spectators of a fire and is a frequently documented factor in egress while people are being entertained [25].

Table A.5: Decisional Behaviours of High-Motivation (Rainfall) Egress

Time in videos (m:ss)	*Decisional Behaviours Observed*
0:00 -0:08	• Rain approaches. Employees open gates at 0:00, where game is suspended by announcer at 0:03, rain encompasses stadium by 0:08. Evacuation is largely simultaneous at suspension announcement. • There are few (<10) who while seated pull out umbrellas, about 20 who do not have umbrellas stay seated. • Majority go to closest gate relative to seating.
0:08-0:19	• As congestion at some gates begins (climbing rapidly to 120 ped/min/m), there are 4.5% of the pedestrians that do not use the closest exit and switch gate destinations on their journeys. At this point, queuing develops at all gates. Queues range in length to about 5-10m. Queues are directed against the wall as there is some shelter there. • People are carrying possessions including food. • Elderly people seen clearing a path in queues with walking stick, hitting others out of the way. • At approximately 15 seconds 97.5% of the population is in movement.
0:19-0:20	• Rain intensifies. Spectators who remained seated without umbrellas begin to evacuate.
0:20-2:45	• At 0:20, peak congestion is seen which steadily decreases until the stadium bowl is empty at 2:45. Those with umbrellas remain committed to their seats.

Figures A.5 and A.6 describe the percent population egressed with time and the flow of persons per minute per exit width with time for the standard and high-motivation egresses, respectively. The timelines can also be referenced with Tables A.4 and A.5 above, for detailed time markers and event descriptors which correlate to the observed max peaks seen based on specific events seen in the stadium egress. Figure A.3 is helpful for reference as it illustrates an observed gate.

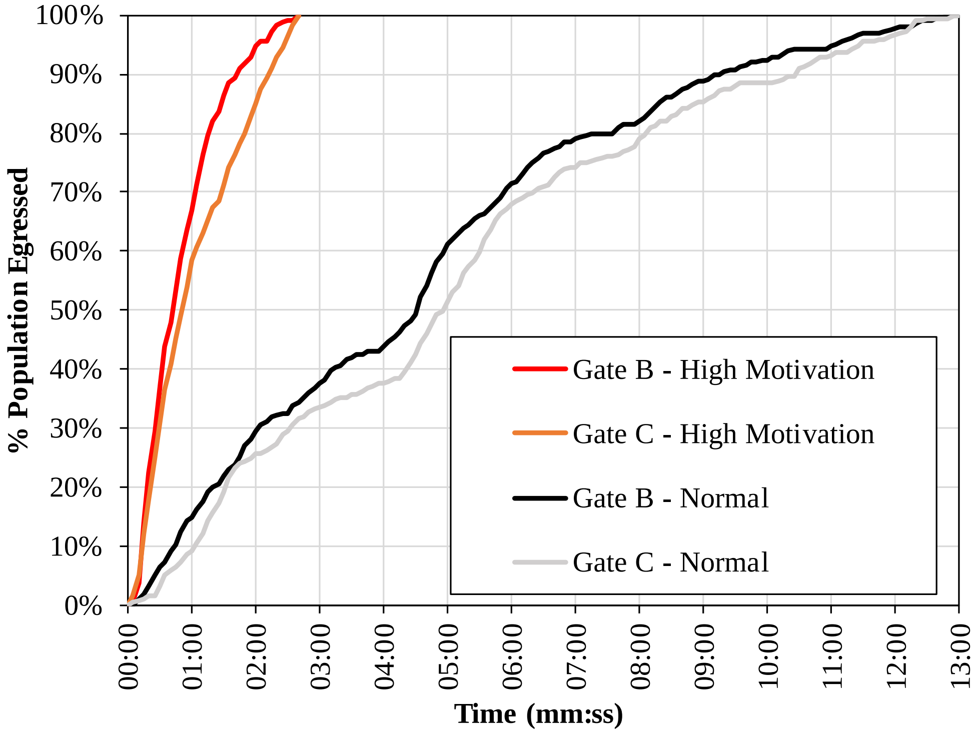

Figure A.5: Percentage of population egressed for Normal and High Motivation Stimuli

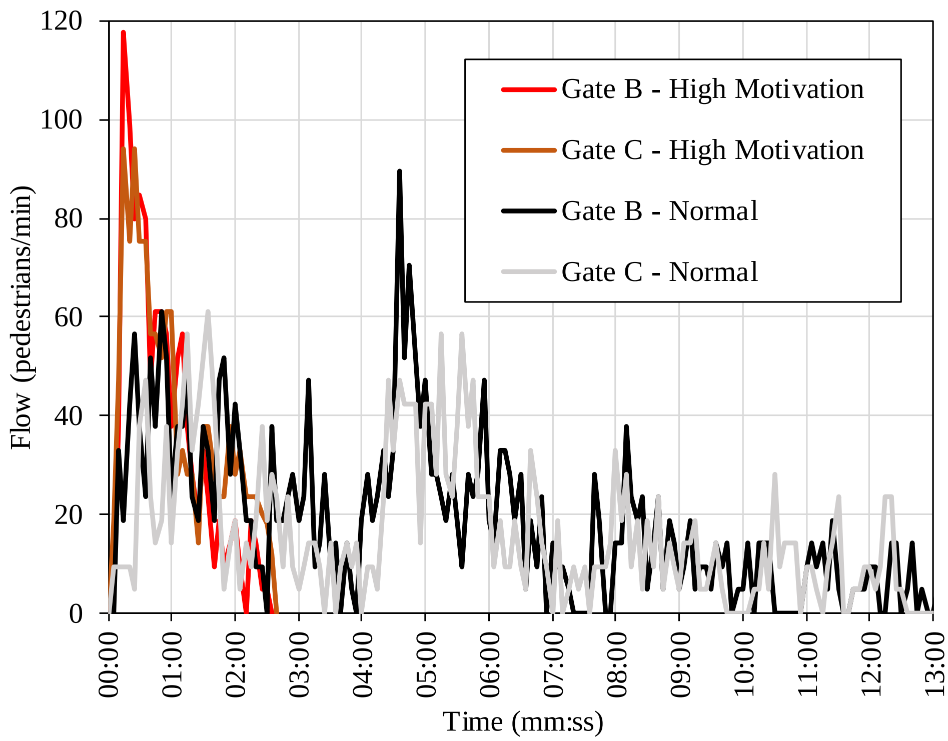

Figure A.6: Flow at Gate for Normal and High Motivation Stimuli

The normal post-game egress was very long and distributed (spread out). The first major wave of spectator egress starts at time 0:00 with the completion of the game. Egress slows at around 1:40 as an interview with the winner begins. During the interview, egress slows down. The interview ends at 3:48, cueing applause, followed by the next big wave of spectator egress at 3:57 to 6:50. During this time, the greatest flow is recorded as 89 ped/min/width. From 6:50 to the end, the remaining 20% slowly dissipate. These time markers can be referenced in Table A.4 above.

By direct comparison, the egress behaviour observed for the high motivation rain evacuation displayed a very different trend; the evacuation was faster and steadier. The pre-movement time was overall short (about 10 seconds), with some spectators (about 5%) beginning their egress before the game suspension announcement. The rain quickly intensified, potentially subverting the optimism for spectators that the rain would be minor and leading to a greater incentive for people to seek shelter inside. The persistence of the rain may have acted as a constant evacuation cue to which the spectators were exposed. The greater flow observed is what led to queuing and congestion that was unseen in the regular egress (see next section). It is important to remark that peak densities (120 ped/min/m High motivation and 90 ped/min/m Normal) seemed to be correlated to the announcer calling the cessation of activities of the match regardless of the stimuli. However, the densities were higher with the stimuli despite the lower number of spectators in the stadium.

A.4.1.1 Queuing and Congestion

The observed behaviours described above lead to specific trends in the overall egress of these stadia which are supported with the following quantifiable data. Figures A.6 and A.7 illustrate the accumulation of people arriving at and departing from the exit corridors from the left, right and center aisles of the standard and high-motivation egresses, respectively. For comparison, they are scaled to the same x and y axes. A visualization of a gate is provided in Figure A.3.

The standard egress event exhibited a higher volume of people. This, together with the dispersed egress patterns due to post-game announcements and the relatively slow movement due to low motivation, caused moments of temporary congestion throughout all walkways. However, there were no accounts of quantifiable queuing (Figure A.7). Pedestrian movement was often impeded because of the overall higher number of people and other spectators choosing to relocate and loiter (a behaviour not seen in the rain evacuation). Although this caused moments of congestion due to a reduction in passageway width, flow was overall maintained which led to no accounts of queuing. Figure A.7 illustrates this, in which there are no deviations between the arrival and departure lines, meaning that no person was ever waiting in a lineup to exit through these gates.

Conversely, the rain event exhibited congestion and queuing formations, particularly around the gates despite the significantly lesser population. This was because of the fast, immediate and simultaneous evacuation. Queue development is illustrated in Figure A.8 when the amount of people arriving at the gate surpasses the amount of people that have exited the gate. This queue can be quantified by the difference in these two values (arrival at the gate and departure through the gate).

The flow rates for pedestrians is different based on the direction of approach and location relative to where the audience was sitting. Figure A.7 illustrates the difference in flow rates for each direction through Gates B and C. For both gates, the flow from the center is low compared to the left and right entrance flows. This is because spectators entering from the center were limited to using the stairs directly in front of the gate. As seen in Figure A.3, these stairs do not serve all rows, and only provide access to a smaller triangular section of seats on either side, compared to the other seating sections. The left and right flows accommodate multiple sets of stairs serving larger sections, and thus a greater number of pedestrians were observed using these.

This effect carries over into the high-motivation egress event. The lower demand of the center stairs led to overall lower flows approaching both gates from the center. Furthermore, little to no congestion or queuing was observed on this approach, compared to the higher congestion observed on the side approaches.

The flow rates for each gate's side differs, with the left approach for Gate B being more popular than the right approach, and the right approach being more popular for Gate C. This also carries through in the high-motivation egress. This is likely due to the seating locations of the spectators. The stadium is highly symmetric, but the rows extend down further on either side of the court as seen in Figure A.3. These additional rows increase the number of spectators in these sections, and thus increases traffic when the spectators egress. As seen in Figures A.8 and A.9, Gates B and C are located on either side of this larger section, and the increased popularity of each gate's side corresponds to the location of the larger section.

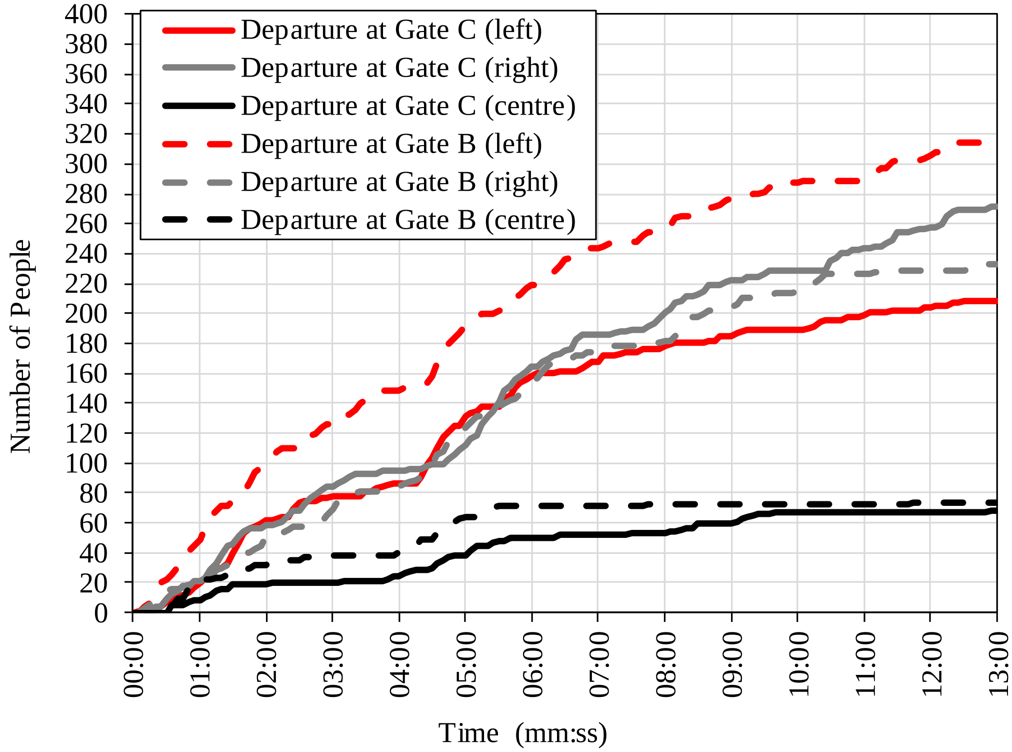

Figure A.7: Cumulative arrival and departure for the standard egress at Gate B and C

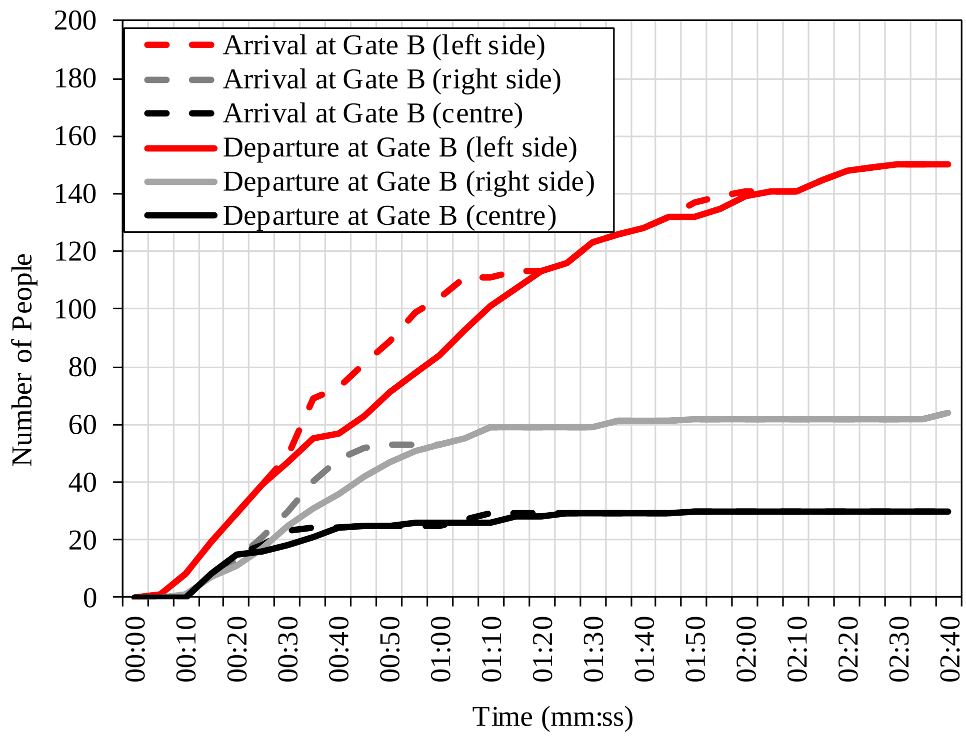

Figure A.8a: Cumulative arrival and departure for the high-motivation egress at Gate B

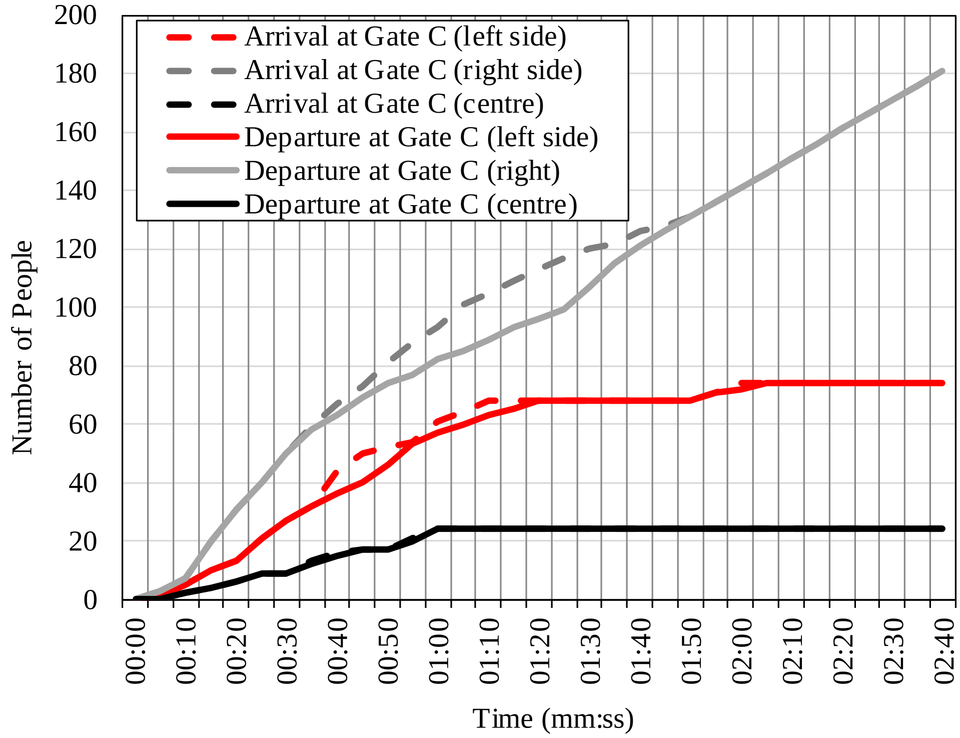

Figure A.8b: Cumulative arrival and departure for the high-motivation egress at Gate C

A.4.1.2 Wayfinding

Figures A.9 and A.10 describe exit use distribution during egress. They were developed through tracking occupants from their seat location to the exit they chose in each of the videos. With this, these figures illustrate the percentage of spectators in each respective section who chose to egress at their assigned gate (denoted by straight arrows), and the deviating percentage of spectators in that section that chose a further egress path to the next closest gate (denoted by curved arrows).

The regular and rain egress showed similar behaviour in wayfinding, whereas the rain evacuation showed more defined and systematic trends. The regular evacuation showed more deviation in the way people chose to exit. In both cases, most people used the closest exit.

Those who did not pick the closest exit instead chose the next closest exit, which was found to be the corridor that they first entered. Hence, primary choice of wayfinding is to the nearest exit or whichever is most familiar to them that the entered from. With this, it was found that the crowds migrated towards the direction of the main entrances (Gate A, B and C, where the only 2 elevators are located in the back concourse). These findings are attributable to behaviours outlined in Tables A.4 and A.5. These behaviours may serve as examples of familiarity to choose the most familiar exit.

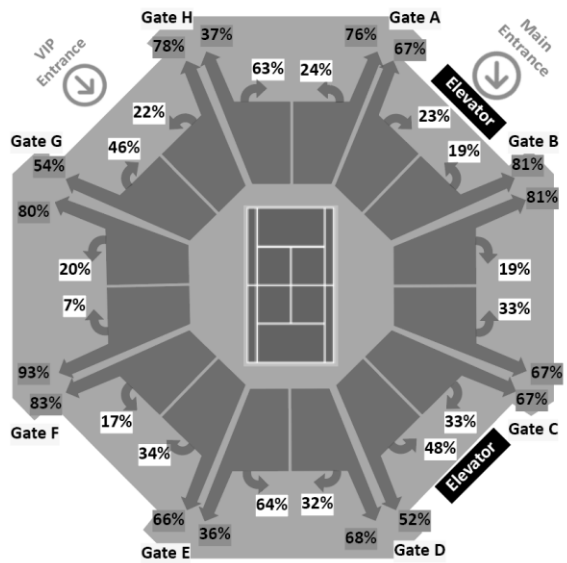

Figure A.9: Exit use distribution for the standard egress.

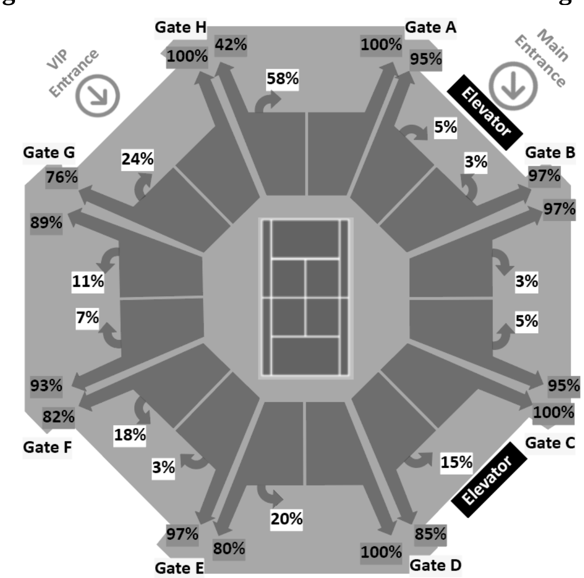

Figure A.10: Exit use distribution for the high-motivation egress

A.4.2 Emergency (Fire) Egress Study

As ethical considerations prohibited an emergency evacuation of the tennis stadium, the authors supplement motivational comparison with the observations from a Canadian football stadium they had access too. That stadium had a small isolated fire (the fire did not spread beyond its point origin in the stands). So as to be conscious of its representation and reinforce behavioural findings, this event is then compared to the analysis of a North American football stadium fire and historically to a European Football (soccer) stadium to verify behavioural and management description findings. As footage is not strategically filmed to quantify all aspects of density, only a qualitative in nature timeline is available for these case studies as a quantitative analysis is not possible.

A.4.2.1 Canadian Football Stadium Fire

The total recorded egress was analyzed over 2 minutes 55 seconds for the fire evacuation at this stadium. A timeline is presented in Table A.6 with visual references to Figure A.11. This was attributable to the time it took for approximately 120 spectators to evacuate the local stands from the time that smoke was visible. The origin (00:00 time) is taken as the earliest available footage the authors obtained, when the fire had already been lit and dark smoke was emanating from the stands. Despite visible smoke and flames, non-involved fans did not begin to egress until the small explosion was observed, over 35 seconds after the start of the video footage, and more than 30 seconds after fire was visible. The smoke appears as though it did not act as a cue to evacuate, as it was only when an explosion was observed that pedestrians were seen to move. This may be an example of normalcy behaviour, as the spectators could have thought that the situation was somewhat low-risk and normal. In sports culture, particularly in Europe, the lighting of flares by fans is not uncommon for certain clubs [26]. Even after the explosion, most spectators only shifted over a few seats, and it took a few seconds for another group of spectators to start their egress. 16% of spectators were observed filming the incident on their phones, sometimes blocking egress routes or even getting closer to the incident. This may also be an example of optimism, as those who chose to film likely assumed that they could do so somewhat safely, and that there was no danger present in doing so. This could also be attributed to bandwagon behaviour, as one person filming influences another and so on. Additionally, this could be an example of attentional behaviour as spectators are focused on the event as it unfolds, missing potential cues as the situation evolves. An illusion of control can be observed after the banner catches fire, as some members attempt actions to keep their fire under control, despite lacking a fire extinguisher. Bandwagon and authority behaviours were also seen as most masked individuals stayed together in the stands, with some following one flag-bearer when he made his way to the exit. The authors though suggest that the behaviour being seen is more akin to a social identity being developed among the fire setters (see reference [27]). The behaviours seen in this study can be supported by very similar behaviours presented at two notable case studies – the recent 2019 fire at Nissan Stadium, and the historic fire at Bradford City Stadium in 1985 – discussed further in the following subsections.

Table A.6: Decisional Behaviours of Emergency Egress for Canadian Football Stadium

Time in videos (m:ss)	*Decisional Behaviours Observed*
0:00 -0:15	• Dark smoke begins to emanate (0:00). Spectators are not evacuating at this point. By 0:06, fire is now visible. By 0:15, a flare is thrown on the field.
0:15-0:28	• Staff arrives to remove the flare from the field and spectators are seen dancing (now masked).
0:28-0:35	• An explosion is heard, and most spectators are now evacuating. Some remain close to the fire and begin to film. Some not filming are fixated watching the fire without filming.
0:36-0:50	• Additional people begin recording the fire, egress in the northern portion for the stands (direction of smoke plume) is well underway. • Spectators are seen carrying bags and possessions in egress.
0:51-1:02	• Some spectators evacuating to the east are blocked by masked spectators with a large flag which at 1:02 catches fire.
1:02-1:08	• Spectators attempt to remove fire source underneath large flag. Staff begin fighting fire with extinguisher. Masked spectators begin tearing up flag but fire spreads. Spectators continue to film.
1:08-1:22	• Security staff suppresses fire.
1:22-1:52	• Spectators continue dancing in stands (see Figure A.11a). Staff members begin directing those remaining sitting to egress.
1:52-2:07	• Second explosion is seen when staff member lifts trash can lid. Remaining masked participants begin to exit on direction of staff and follow flag bearer (see Figure A.11b).
2:07-2:55	• Last remaining people in stands are cleared out.

Figure A.11a: Masked participants remaining in stands despite banner on fire

Figure A.11b: Masked participants remaining in stands following flag-bearer to egress

A.4.2.2 Pyrotechnic Machine Fire at Nissan Stadium

On Sunday September 15, 2019, a pyrotechnics machine caught fire on the field of a National Football League Match in Tennessee's Nissan Stadium. Similar to the analyses performed on the Canadian football stadium fire, the authors' access to credible and comprehensive footage of the case study is limited to publicly shared recordings and photos (these do not have clearances though for publication but are readily found upon reasonable online searches at the time of writing).

Similarly, it is noted that the initial stages of the fire and the associated human behaviours cannot be considered since the available footage only commences when the fire has already reached a substantial size. It is also noted that this fire propagated more rapidly than usual as a result of the highly combustible and readily available fuels of the machine. The event fortunately caused no casualties or reported injuries. In both events, the game was not stopped.

In turn, this case study reveals similar occurrences of pre-movement and egress behaviours outlined as seen in the Canadian football stadium. Table A.7 describes the observed behaviours in a timeline of key events. The origin (00:00 time) is noted to be the earliest available footage, at which time the machine has been entirely engulfed in flames, and the resulting smoke is directly affecting the nearby stands.

Table A.7: Decisional Behaviours of Emergency Egress for American Football Stadium

Time in videos (m:ss)	*Decisional Behaviours Observed*
0:00 -0:04	• Fire engulfs the machine with thick black smoke. Security is on scene quickly but is not directing evacuation. Players and spectators are not evacuating and begin watching the fire.
0:04-0:19	• Staff begins moving combustible objects away from the machine, photographer approaches the fire for a photo. At 0:06, a staff member attempts to put out the fire with an extinguisher. At 0:07, a second photographer approaches. At 0:19, the fire extinguisher runs out of substance and the staff member then begins to order spectator to evacuate.
0:20-0:26	• Evacuation begins, but many spectators do not follow directions. This tends to be in localized groups in the stands. Spectators can be seen filming with their cell phones.
0:27-0:40	• Fire decreases in size by about 3 x the surface area. Staff attempts to fight fire further, but extinguisher is out. By this time, the first five rows are evacuated. Some begin trying to come back to their seats.
0:40-0:50	• Visible fire is put out by staff.
0:50-1:08	• Smoldering fire is put out and spectators allowed to return.

A.4.2.3 Bradford City Stadium Fire

On Saturday May 11, 1985, a lit cigarette ignited the wooden stands of the Bradford City Stadium, causing a rapidly growing fire during an English League match. The fire and resulting smoke engulfed the entire stand in less than four minutes, resulting in 56 casualties and an additional 265 non-fatal injuries. The Bradford City Stadium fire was well documented as recorded by Yorkshire Television followed by investigation from the Popplewell inquiry [28]. The fire severity of this particular incident is much greater than that seen in the other stadium fire case studies but does share similarities from a management and behaviour perspective. Table A.8 identifies behaviours observed in reference to recorded footage. The origin (00:00 time) is noted as 3:44 PM, when the fire grew to the stands. At this point, the fire was significantly noticeable.

Table A.8: Decisional Behaviours of Emergency Egress for Bradford Football (Soccer) Stadium

Time in video (m:ss)	*Decisional Behaviours Observed*
Prefilm [26]	• Archived photography illustrates the beginning of the fire. It illustrates smoke emanating between laminate boards in the stands. Local egress has occurred, but several fans are watching the smoke and development about 1m away. Photos are being taken.
0:00-0:12	• Fire is seen in the film and is identified by the TV commentator. It can be seen people are moving away from the fire, but they stop short of the entry to the field. Police are prompting people and directing them away from the fire and then on the field. Away from the fire in the stands, nearby people continue to watch the match as it is still in play.
0:12-0:24	• People in stands away from the fire move closer to the smoke to appear to investigate. Smoke is getting thicker.
0:24	• Game is stopped. People now enter the field.
0:24-0:47	• Spectators are jumping the wall to the field. People are observed being trampled in this process if they fall. The fire now has engulfed about 6 rows. People elsewhere are cheering for the game as they are being evacuated. Spectators are also watching the fire develop.
0:47-1:22	• Smoke is dense and takes over the whole stand. Spectators are observed helping each other over the wall and onto the field.
1:22-1:40	• Roof is now on fire. At this stage, people are still attempting to get onto the field but heat from the fire is now affecting the spectators and harming them.
1:40-2:27	• Field area in immediate area of the fire is now been cleared of people. At the mid-section, it is still clearing.
2:27-3:00	• Crowd on field is mostly staying in the location they are, people are still leaving the furthermost sections. By 3:00, an elderly person is observed being dragged out of the stands.
3:00-3:25	• Stands completely engulfed.
3:25-4:15	• There are people still evacuating stands, though footage shows people in the fire. Police officers are filmed directing spectators to assist in evacuation. 15 people help put out a fire on a man.
4:15-4:49	• First responders arrive on scene and footage concludes.

A.4.3 Observed Similarities and Differences between Studies

Similarities can be drawn between the three egress stimuli studies. All three took place in a Canadian sporting stadium and resulted in an effectively complete egress of spectators. Of the two non-standard egress events, both occurred under high-motivation stimuli (rain and fire). All scenarios included some degree of influence of authority to prompt or influence evacuation, whether from announcers or stadium staff themselves. However, significant differences were also observed with regards to total egress times, pre-movement, behaviour, and observed congestion.

Despite the significantly larger population and size of the rain event, total egress times were less than the observed time for all of the emergency fire events considered. The authors believe that this is heavily influenced by the perception of threat communicated by the authority figure – for example, in all fire case studies, the size of the fire correlated to the urgency of the staff to evacuate spectators. The stimuli of the rain also affects all people in the stadium which may have caused increased congestion of all egress routes whereas the fire event was a highly localized event so levels of high motivation were differently spread between the two events. Higher pre-movement times in fire scenarios contributed to the longer egress times, though where staff was unsuccessful in having members within the stand leave which possibly leads to the role of social identities and group formations within the stands (i.e., those filming or those causing vandalism for small examples).

In the Canadian Football Stadium Fire event, for example, some members of the population were actively participating in the events leading up to the fire. This resulted in a longer egress time for these members as they had to be directed, both by staff members and the leader of their group, to evacuate the stands. This took some time, as a fire in the stands was not expected nor necessarily planned. In contrast to this, the suspension of play due to rain in a tennis game is an expected occurrence as rain was forecasted, therefore the event was potentially expected by both spectators and staff. Staff response in this case was also much quicker, with play suspended only a few seconds after the initial start of rainfall, and some spectators standing to leave even before the suspension of play was announced. The egress during the rain event was implied through standard procedure and an announcement by the Chair Umpire. The Chair Umpire's announcement to suspend play has an effect of directing the audience how to act. In the case of the rain event, this appears to have induced the evacuation process for most of the audience. In the case of the normal egress, it delayed it and contributed to congestion and cross flow. Similarly, during the Bradford fire, police officers directed evacuees to enter the pitch, influencing the route evacuees took – but this was only followed upon when the game was stopped. These are examples of Authority bias. Conversely, the lack of instructions from a figure of authority can have a delaying effect, as observed in the standard egress which came with no explicit instructions on when to leave, or the Nissan and Canadian football stadium fires where authority figures did not direct egress until after attempting to put out the fire. For example, the reaction of authority was much faster than that observed with the Canadian football which is likely due to the size of fire observed and associated threat.

The major behaviours of the emergency event, namely attentional, optimism, and bandwagon behaviours were observed in all scenarios. However, these behaviours were not as widespread, and the effects manifest in slightly different ways. Similar to the fire event, attention played a role for some spectators who continued to watch the tennis game even as the rain started to fall. However, this was quickly subverted by the announcement of suspension of play. With the item holding the attention removed by an authority figure, the decision for many could have switched from stay to evacuate. However, this does not mean all spectators evacuated. Optimism behaviour also likely played a role for some audience members who chose to stay in their seats with umbrellas and try to wait out the rain. However, as the majority of the audience chose to evacuate, bandwagon behaviour may have encouraged many of those who initially tried to wait out the rain to evacuate as well.

In the standard post-game egress, potential attentional and bandwagon behaviours were also observed, as multiple rounds of applause and events caused leaving spectators to pause and, in some cases, return to observe post-game activities in the stadium. This had a positive effect on egress in this scenario, as it reduced the flow of people through the exits and preventing queuing from occurring.

Pre movement behaviors also substantially differed between the events, for example at 15 seconds 97.5% of the population was in movement towards an exit in the rain event compared to 8% of the population in the regular end game egress. It would not be until over 4 minutes for an equivalent majority of the population to be in movement in the regular end game egress.

During the actual egress of the rain event, several spectators were observed running to the exit. This is a high contrast to the Canadian Football Stadium and Nissan Stadium fire events, where spectators were only observed walking to the exits. In the Bradford Fire, running was also observed as spectators egressed onto the field. This may have been due to the persistent and unpleasant egress cue delivered by the falling rain in the rain event, and the heat from the large fire in the Bradford event. Planning fallacies may have played a role in both of these events, as in both cases the hazard arrived quickly, leaving very little time for the spectators to evacuate once they started to experience the hazard.

It is important to also note the cultural and demographic differences present in each event, as the audience of a football match likely has a different demographic distribution compared to a tennis match. The audience members involved in the fire events appeared to be young adults and adults, whereas both events at the tennis stadium consisted of a much more diverse population, with families and seniors also observed in larger numbers. In terms of movement, observations from the fire event show that their pre-movement times can be longer than expected, especially if an individual is a member of a group closely involved in the situation. Cultural implications can have an additional effect through anchoring behaviour. During standard post-game egresses, cultural expectations of post-game events can distribute the pedestrian demand over a longer period of time to prevent crowding. Conversely, this can have negative effects in emergencies, with the football culture of not going onto the pitch causing some delay in getting evacuees to evacuate onto the pitch during the Bradford fire.

A.5 Future Research

A.5.1 Recommendations for Future Studies

The examination of multiple egress types has highlighted the importance of considering the hazard and environmental factors in emergency egresses as they may influence the behaviour of evacuees. The variation between different hazards and stimuli may potentially alter premovement times, decision-making, and flow rates. However, these hypotheses cannot be confirmed given the limited number of scenarios, trials, and observations herein. Thus, there are several potential avenues for future needed research to further validate, refine, and expand upon this work.

Additional scenarios and trials are needed to generate more observations to validate the observations made here. In order to do this, a methodology to standardize experiences is needed, allowing the comparison of similar or identical scenarios to make robust conclusions. This is a considerable challenge as fire scenarios in stadia are rare, and do not occur in a controlled environment where all variables can be kept constant. Rain events and other adverse weather events that would cause a high-motivation egress are more common, but architectural, population, and demographic differences may still exist. It may be useful to create a method for archiving footage of abnormal egresses in stadia, even if using third-party sources such as cellphone videos and security footage to collect the data.

Other scenarios not studied in this paper but may still be of interest include terrorism and presence of explosive devices, as these scenarios are extremely rare but also are likely to result in different behaviours. The role of authority figures and staff should also be examined in more detail to see how their actions affect stadium attendees during emergency egresses, and what role information from announcements, signage, or trained staff has to play. This would not only be useful for confirmation and validation for modelling, but also for the development of more effective evacuation methods, techniques, and technology.

Different cultures across the world may also lead to variations in how stadium attendees behave and move. These cultural differences should be looked at in detail and may warrant its own independent research to determine how applicable data from abroad can be applied to similar scenarios involving a more local population, not just in evacuation of stadia, but evacuation and circulation in general. These are just some examples of potential additional research that can be done to help reveal and confirm the factors affecting pedestrian egress.

A.5.2 Recommendations for Future Evacuation Modelling

Human behaviour is important to consider when constructing computer models of stadia for egress. The congestion and high traffic volumes observed during the rain evacuation further highlights the need to model evacuations and egresses to ensure suitable designs. It also exemplifies the need for modellers and practitioners to understand the role of the authority figures such as staff and announcers in the stadia.

Practitioners' models should account for a specific range of scenarios that will influence human behaviour in egress. In some cases, environmental conditions for open aired stadia need to be understood in association to egress. It is noted that these behaviours and staff roles noted herein were determined using limited data from only a few events, limiting the results to similar scenarios and stadia.

Inputs regarding pre-movement delay is one of the main egress parameters and is affected herein by the authority figures. For example, when modelling a fire egress, the pre-movement times may be impacted by spectators who delay their evacuation to take photos or continue to watch the game if it is still ongoing. This lack of movement can be observed especially if the fire is in the early stages or is further from the spectators. Standard post-game egresses can also be very spread out and in excess of minute rules in guidance and standards, especially if post-game events and activities are held – though these will occupy the spectators during egress, minimizing anxieties, but may also introduce distractions and cause injuries just the same as crowding, and congestion on stairs, walkways and exits can still occur. In high motivation exits where play is stopped and an external stimulus supplied (rain in this case), pre-movement times may be negligible and a simultaneous evacuation may take place.

Route choices are also affected by behaviour, as observed through exit selection. In both the standard and rain egresses, most spectators tended to use the closest exit (rather the exit they came in). In the recorded rain event, it was also seen that spectators tended to maintain a chosen route towards their target exit, which rarely changed even as other exits or pathways became less congested.

Social identity influences the decision to evacuate; evacuation is delayed if others are similarly not evacuating or the group is participating in part of an activity. Conversely, the choice to evacuate sooner could be made if others nearby also start evacuating. This also applies to standard post-game egress, with some audience members staying around and others choosing to leave.

While it is beyond the scope of this paper to represent movement speed and anthropometry data, this will be needed in the light of dated movement speeds that do not represent the demographics seen in stadiums today or may not be tailored for stadiums. That topic area is currently under development by the authors elsewhere [15].

A.6 Conclusions

This study examined the egress of stadium patrons under several different motivational conditions, using footage collected at Canadian stadia. The footage was analyzed by multiple researchers to determine flow rates and actions taken by stadium patrons under the different conditions (Normal, Rainfall, Fire). By comparing the results of the three different egress motivational conditions and their stimuli, several key findings were revealed and determined:

- The egress of stadium stands differs depending on the nature of the motivational scenario but evacuation is influenced by actions and directions of authority figures;
- Movement through the stadia is heavily influenced by normality, attentional, optimism, and bandwagon behaviours;
- During a standard post-game egress, spectators are more likely to take longer to initiate their egress if post-game activities are still occurring on the field. This can cause congestion on passageways as they stop to congregate;
- Despite egresses taking longer in normal conditions than would be specified in guidance, there was no evidence of visible anxiety in the spectators in this process;

- During high motivation scenarios, faster evacuation and higher traffic volumes were observed with greater congestion at exits being observed compared to normal evacuation;
- The differences between the high-motivation rain event and the fire events were potentially influenced by the state of play on the field, as play was not stopped during the fire event. Furthermore, there was an absence of a dominant authority figure ceasing the activities during the fire event; and
- The rain event was found to have lower pre-movement, faster walking speeds, and a shorter evacuation time despite the higher volume of people. Differences here could be attributed to longer pre-movement times in the fire scenarios, which can be further attributed to formed social identities in the crowd (those that investigate, those that leave, and those that participate in vandalism for some examples).

The data presented herein is novel and unique. This large-scale field data has been comprehensively gathered to determine and reveal qualitative behavioural data and quantify egress pattern data. The data has been post-processed to minimize bias in interpretation. The data is indeed helpful now to form initial input assumptions and to design stadia egress and evacuation models. However, this is a first stage study, meant to be built upon where future research should consider utilizing data from multiple egress scenarios to confirm the observations seen. This manuscript's findings are limited to similar scenarios and stadia, as discussed within the limitations of the study, as only one trial of each scenario could be observed. A database of case studies across a diverse set of hazards and egress conditions, behavioural observations, and movement speed profiles would be immensely useful in reducing uncertainty around future predictive egress and evacuation modelling where validation and verification will be needed. This is recommended as a second stage of this research.

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Appendix B: Profile Generator Alpha 0.7 VBA Code

```
‘*******************************************************************
'Profile Generator Alpha 0.7

'Timothy Young

'This program reads Kinovea Trajectory .txt files and generates movement speed profiles based
on tags supplied in the ‘name’ field, separated by spaces.

'WARNING: Profile Generator is still under active development and should not be used in
engineering applications as it has not been validated against true movement speeds. The author
provides this code and the generated data as is and is not liable if the user misuses the data
provided or if the code causes damage in any way, nor are they liable for any errors or
deficiencies in the code or data. The author does not warranty the completeness, accuracy,
content, or fitness for any particular purpose or use of any data or code made available here, nor
are any such warranties to be implied or inferred with respect to the data sets furnished herein.
This code and resulting data is to be used with caution. In all cases designers should consult the
thesis for accuracy and exercise their own engineering judgement in utilizing the code and data.
'*********************************************************************

Public nofile As Integer
Sub Calcspeed()
'
' Calcspeed Macro
' Calculates instantaneous and average velocities from Kinovea Outputs. Import Kinovea file
starting from line with #

'
' Initial Setup. Define variables, Goto first cell, add headers.

    Application.Calculation = xlAutomatic
    nofile = 0
    Dim framerate As Double
    framerate = Range("G12")

    Dim framedrop As Double
    framedrop = Range("G13")

    Dim tagcount As Integer
    tagcount = Range("G14")

    tagsdone = False
    Call OpenTxt
```

```
    If nofile = 1 Then
    GoTo nofileexit
    End If

    ' First 3 rows contain no useful data in kinovea output file. Delete these lines.
    Rows(1).EntireRow.Delete
    Rows(1).EntireRow.Delete
    Rows(1).EntireRow.Delete
    Rows(1).Insert
    'Get framerate from user input. Default is for a 11.92 FPS security camera system. Kinovea is
able to read and display the framerate.

    'Dim AgentProfile As String
    Dim AgentProfile As Collection
    stepdone = 0
    profilecount = 0
    profiledone = 0
    'Set Up Headers
    ActiveSheet.Range("A1").Select
    ActiveCell.Offset(0, 4).Range("A1").Select
    ActiveCell.Value = "xChange"
    ActiveCell.Offset(0, 1).Range("A1").Select
    ActiveCell.Value = "yChange"
    ActiveCell.Offset(0, 1).Range("A1").Select
    ActiveCell.Value = "Frame Distance"
    ActiveCell.Offset(0, 1).Range("A1").Select
    ActiveCell.Value = "Inst.Velocity"
    ActiveCell.Offset(0, 1).Range("A1").Select
    ActiveCell.Value = "Total Distance"
    ActiveCell.Offset(0, 1).Range("A1").Select
    ActiveCell.Value = "Avg. Velocity"
    ActiveCell.Offset(1, -9).Range("A1").Select

'Main Calculations code. Loops until no more data found.'
    Do While stepdone = 0
    If IsEmpty(ActiveCell.Offset(1, 0)) = False Then ' Not a gap cell, get agent type, then proceed
down 1 to calculate data

        If Not tagsdone Then
            Set AgentProfile = New Collection
            For i = 1 To tagcount
                If IsNumeric(ActiveCell.Offset(0, i)) = False Then
                    AgentProfile.Add ActiveCell.Offset(0, i).Value
                End If
            Next i
```

```
        tagsdone = True
        firstrow = True
        Calculate
    End If

    ActiveCell.Offset(1, 3).Range("A1").Select ' Calculate framecount starting at 1

    If firstrow Then  'first row of data. only calculate x and y coordinates
        ActiveCell.FormulaR1C1 = "=1"
        ActiveCell.Offset(0, 1).Range("A1").Select
        ActiveCell.FormulaR1C1 = "=RC[-3]"
        ActiveCell.Offset(0, 1).Range("A1").Select
        ActiveCell.FormulaR1C1 = "=RC[-3]"
        ActiveCell.Offset(0, -5).Range("A1").Select
        firstrow = False
        Calculate
    Else 'Not the first row, can calculate xChange, yChange, distances travelled, and velocity
(both instantateous and average)
        'Manual Calculation only after this point
        Application.Calculation = xlCalculationManual
        ActiveCell.FormulaR1C1 = "=R[-1]C+1"
        ActiveCell.Offset(0, 1).Range("A1").Select
        'Calculating Change in X
        ActiveCell.FormulaR1C1 = "=(RC[-3]-R[-1]C[-3])"
        ActiveCell.Offset(0, 1).Range("A1").Select
        'Calculating Change in Y
        ActiveCell.FormulaR1C1 = "=(RC[-3]-R[-1]C[-3])"
        ActiveCell.Offset(0, 1).Range("A1").Select
        'Calculating average distance
        ActiveCell.FormulaR1C1 = "=SQRT((RC[-2])^2+(RC[-1])^2)"

        'Framedrop Detection Module (Currently Disabled)
*******************************************************************************
       ' If framedrop <> 0 Then
        '   If ActiveCell < framedrop Then 'Check if average distance is less than minimum
frame distance. If so, remove row.
         '  Rows(ActiveCell.Row).EntireRow.Delete
          ' ActiveCell.Offset(-1, -6).Range("A1").Select
          ' End If
        'Else

        'Framerate above threshold, continue.
        ActiveCell.Offset(0, 1).Range("A1").Select
        ActiveCell.FormulaR1C1 = "=RC[-1]/(1/" & framerate & ")"
        ActiveCell.Offset(0, 1).Range("A1").Select
        ' Calculating average speed
```

```
        ActiveCell.FormulaR1C1 = "=R[-1]C+RC[-2]"
         ActiveCell.Offset(0, 1).Range("A1").Select
         ActiveCell.FormulaR1C1 = "=RC[-1]/(R[-1]C[-6]/" & framerate & ")"
        ActiveCell.Offset(0, -9).Range("A1").Select

       ' End If

    End If

  Else 'Gap cell detected, perfect place to put average speed of entire trajectory. Place in correct
column for demographic.
  Calculate
  tagsdone = False
  'save place to come back to later

  rowAvg = ActiveCell.Row

  'Search K->Z for column, max of 15 different profiles (CAN BE CHANGED IF NEEDED).
  For Each Tag In AgentProfile
    With Worksheets(1).Range("k1:zz1")
    Set col = .Find(Tag, SearchDirection:=2)
    If col Is Nothing Then

      ActiveSheet.Range("k1").Select
      Do While IsNumeric(ActiveCell.Offset(0, 1)) = False
        ActiveCell.Offset(0, 1).Select
      Loop
      ActiveCell.Offset(0, 1).Select
      ActiveCell.Value = Tag
      profilecount = profilecount + 1
      colIndex = ActiveCell.Column - 1 'Index value for where average with AgentProfile
name should be delivered.

    Else
      colIndex = col.Column - 1
    End If
    End With

    ActiveSheet.Cells(rowAvg, 1).Select

    ActiveCell.Offset(1, colIndex).Range("A1").Select
    Dim avgspeed As String
    Let avgspeed = "=J" & rowAvg

    ActiveCell.Formula = avgspeed
  Next
```

```
        If ActiveCell = 0 Then 'No average detected, therefore dataset has ended. Exit loop and
display message.
            ActiveCell.Delete
            stepdone = 1
        Else 'Return to column 1, next row down should be a # to start next trajectory
        ActiveCell.Offset(1, -colIndex).Range("A1").Select
        End If

    End If
    Loop

    'Statistical Distribution Analysis Runs after Speed Generation Completed.

    'Find furthest data column

     ActiveSheet.Range("L1").Select
     Do While stepdone = 1
        If IsEmpty(ActiveCell) = False Then
            ActiveCell.Offset(0, 1).Range("A1").Select
            Else
            stepdone = 2
        End If

     Loop

     'found empty cell, go one more over and start data rows.
     ActiveCell.Offset(1, 1).Range("A1").Select
     ActiveCell.Value = "Min"
     ActiveCell.Offset(1, 0).Range("A1").Select
     ActiveCell.Value = "Max"
     ActiveCell.Offset(1, 0).Range("A1").Select
     ActiveCell.Value = "Mean"
     ActiveCell.Offset(1, 0).Range("A1").Select
     ActiveCell.Value = "Std"
     ActiveCell.Offset(1, 0).Range("A1").Select
     ActiveCell.Value = "N ="

    'Start filling in Columns

     profileOffset = profilecount + 2
     Do While profiledone < profilecount
        ActiveCell.Offset(-5, 1).Select
        ActiveCell.FormulaR1C1 = "=RC[" & -profileOffset & "]"
        ActiveCell.Offset(1, 0).Range("A1").Select
```

```
        ActiveCell.FormulaR1C1 = "=MIN(R[-1]C[" & -profileOffset & "]:R[32000]C[" & -
profileOffset & "])"
        ActiveCell.Offset(1, 0).Range("A1").Select
        ActiveCell.FormulaR1C1 = "=MAX(R[-2]C[" & -profileOffset & "]:R[32000]C[" & -
profileOffset & "])"
        ActiveCell.Offset(1, 0).Range("A1").Select
        ActiveCell.FormulaR1C1 = "=AVERAGE(R[-3]C[" & -profileOffset & "]:R[32000]C[" & -
profileOffset & "])"
        ActiveCell.Offset(1, 0).Range("A1").Select
        ActiveCell.FormulaR1C1 = "=STDEV.S(R[-4]C[" & -profileOffset & "]:R[32000]C[" & -
profileOffset & "])"
        ActiveCell.Offset(1, 0).Range("A1").Select
        ActiveCell.FormulaR1C1 = "=COUNT(R[-5]C[" & -profileOffset & "]:R[32000]C[" & -
profileOffset & "])"
        profiledone = profiledone + 1
    Loop

    ' Profile Generation complete.
    'Application.Calculation = xlCalculationAutomatic
    MsgBox "Done Speed Generation!"
    Exit Sub

nofileexit:
    MsgBox "No File Entered."
    Exit Sub
' Turn Automatic Calculations back on
Application.Calculation = xlAutomatic
End Sub
```

```
''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''

Sub OpenTxt()

'Import a text file using Excel's own import function. Code Module by Eric Bentzen, sourced
from https://sitestory.dk/excel_vba/automatic-import-textfile.htm
Dim vFileName

On Error GoTo ErrorHandle
```

```
'The function GetOpenFileName gets the file name without
'opening the file.
'Here we use a filter to display only text files with "*.txt" as
'extension. If you omit the file filter, all files will show.
'Read the VBA help for other options.
vFileName = Application.GetOpenFilename("Text Files (*.txt),*.txt")

'If the user pressed Cancel or didn't select a text file, we exit.
If vFileName = False Or Right(vFileName, 3) <> "txt" Then
nofile = 1
  GoTo BeforeExit
End If

'Switch screen updating off for speed.
Application.ScreenUpdating = False

'We now import the selected text file, and data is
'inserted into a new spreadsheet. If you want to use
'another delimiter than semicolon, you must change
'"Semicolon:=True" to "Semicolon:=False" and set the
'other delimiter (e.g. "Tab") to True.
'I recently discovered that you can avoid
'some formatting problems (e.g. with dates),
'if you add the finel "Local:=True". It depends
'on your local settings and Excel version, but
'the addition does no harm.
Workbooks.OpenText Filename:=vFileName, _
   Origin:=xlMSDOS, StartRow:=1, DataType:=xlDelimited, _
   TextQualifier:=xlDoubleQuote, _
   ConsecutiveDelimiter:=False, Tab:=False, _
   Semicolon:=True, Comma:=False, Space:=True, _
   Other:=False, TrailingMinusNumbers:=True, _
   local:=True

'Just to show how, we auto fit the width of column A.
Columns("A:A").EntireColumn.AutoFit

BeforeExit:
Application.ScreenUpdating = True
Exit Sub
ErrorHandle:
MsgBox Err.Description
Resume BeforeExit
End Sub
```

Appendix C: Raw Data Tables & Sample Calculations

Table C.1: Walking Speeds – Arriving Passengers

10 Mins Late (1st Train)	10 Mins Late (2nd Train)	30 Mins Late	50 Mins Late
0.371934	1.293192	1.268661	1.467035
0.60461	0.955268	1.245869	1.9146
0.67386	0.724256	1.207728	1.817294
0.674006	0.824107	0.981674	1.303677
0.716348	0.773503	1.366906	1.467838
0.718566	1.249304	1.370032	1.204161
0.72384	0.883185	1.649037	1.027584
0.757087	1.212541	1.324565	1.187487
0.804421	1.109608	1.165981	1.550961
0.838787	0.747046	1.031186	1.247515
0.839216	0.922737	1.313845	0.895641
0.848201	1.202634	1.080293	0.982754
0.876164	0.798145	1.421759	1.44301
0.892818	1.123208	1.566298	1.543242
0.893914	0.993901	1.051118	1.412939
0.907195	1.389276	1.049289	1.401804
0.918467	0.960631	0.968577	1.462591
0.928692	1.249897	1.429591	0.789326
1.004664	1.153739	1.299628	1.217411
1.006045	1.074348	1.446049	0.835554
1.020221	1.309609	1.206057	1.332118
1.041451	0.970669	1.664243	1.348253
1.044025	0.906476	1.001385	0.713323
1.080687	1.213923	1.231804	0.925028
1.088808	1.552791	1.194975	1.225976
1.110727	1.01939	1.210472	1.281202
1.113381	1.314067	1.394988	0.719289
1.120634	1.30542	1.578541	0.968932
1.127566	1.073765		1.172232
1.128185	0.978392		1.281719
1.168742	1.23877		1.007308
1.178169	0.957979		0.951853
1.188394	1.509682		1.111818
1.216061	0.989409		1.406971
1.220424	1.452684		1.278631
1.233365	1.209561		1.113159

1.234598	1.367462	1.047259
1.242866	1.318503	1.048636
1.254064	1.118434	1.11701
1.268673	1.369804	1.243806
1.294902	1.543201	1.107525
1.30006	1.204014	1.070203
1.32231	1.174744	0.883406
1.326766	1.069505	1.021046
1.378842	1.277448	0.933779
1.386727	0.875847	1.064449
1.387366	1.161898	0.998374
1.392455	0.951092	
1.401123	0.922709	
1.432581	1.184786	
1.433187	0.802656	
1.461651	1.06805	
1.494229	1.529323	
1.504275	1.445672	
1.557893	1.08847	
1.56119	1.578178	
1.567962	1.563589	
	0.746749	
	1.062448	
	1.12469	
	1.628592	
	1.879729	

Table C.2: Walking Speeds – Departing Passengers

Queueing	*Late to Gate*
0.914353	0.727132
0.954428	0.773658
0.723524	0.88396
0.768746	0.91943
0.941665	0.987785
0.748902	0.991984
0.405857	0.996841
0.851792	1.009836
0.701248	1.078057
0.741522	1.078873
0.779162	1.109074

0.7981	1.120779
0.46853	1.158945
0.771311	1.167461
0.594208	1.181734
1.19424	1.216497
1.010715	1.21809
0.668615	1.232601
0.855668	1.236609
0.740782	1.241052
0.762973	1.255946
0.652271	1.266516
0.966946	1.27734
1.339531	1.333413
0.648398	1.407928
0.699484	1.432629
0.628639	1.460012
0.630483	1.465766
1.293075	1.489755
0.883907	1.502415
0.764525	1.549841
0.991967	1.567599
0.952936	1.596993
1.196063	1.613596
0.755314	1.632881
1.017431	1.639816
0.79339	1.693809
0.901464	1.736284
1.082838	1.817446
0.9169	1.856421
0.97734	1.909277
0.982915	1.909277
1.037166	2.109262
1.075643	2.175799
1.009163	2.29612
1.006844	2.453832
0.946602	2.498456
1.016155	2.65494
1.074483	3.726924
1.091542	
1.109756	
0.911805	
0.868328	
0.894045	

0.829829
0.725906
0.858517
0.995107
0.785462
0.820538
0.780469
0.808957
0.924752
0.923124
0.870268
0.793441
0.7799
0.906101
0.905511
0.91059
1.030176
0.942099
0.804962
0.810849
0.833838
0.905031
0.849889
0.792657
0.767034
0.743187
0.821041
0.895766
0.709684
0.700479
0.557088
0.647154
0.619627
0.672521
0.632172
0.557747
0.844738
0.698435
0.792751
0.665184
0.718336
0.628955
0.578598

0.656121
1.068092
1.032611
0.902627
0.860623
0.996712
1.005966
1.270075
0.836148
0.841642
0.916705
1.036048
1.004923
0.915984
1.34976
1.08672

Table C.3: Walking Speeds – Accessibility Factors

No Factor	*Suitcase*	*Phone*	*Family*	*Mobility Aid*	*Mobility Impairment*
1.567599	1.9092767	1.467837535	1.432629047	0.798100173	0.668615
1.613596	1.9092767	1.247514507	1.333412934	0.594207589	0.371934
1.549841	1.078873062	1.281202099	1.255945723	0.773503167	
1.158945	1.467034714	1.268660723	1.407928014	0.648398037	
1.489755	1.914599823	1.366905597	1.817446331	0.69948404	
2.498456	1.247514507	1.031185508	1.266515878	0.630483473	
1.21809	0.895641143	1.080293359	1.277339555		
1.460012	0.982754135	0.727131947	0.740781936		
1.216497	1.543241542	1.088469736	0.762973082		
0.88396	1.401804377	0.802656038	0.652270805		
1.181734	1.462591427	0.79814529	0.747045694		
1.596993	0.789325542	1.204014044	0.746749184		
2.175799	1.217410834	0.98940929	0.839216167		
0.91943	0.835554453	1.120633543	1.004664023		
2.65494	1.332117836	0.718565947	1.044024812		
2.29612	0.713322608	1.110726983	0.838787005		
2.109262	0.925027537	1.432581383			
1.632881	1.225976415	1.233364996			
3.726924	1.281202099	0.716347817			
1.236609	0.719288815	1.006044679			
1.736284	0.968932171				

1.078057	1.172232495
0.773658	1.281718604
1.817294	1.007308416
1.303677	0.951853366
1.204161	1.111817629
1.027584	1.048636282
1.187487	1.117009622
1.550961	1.107524571
1.44301	1.070203336
1.412939	0.933778809
1.348253	1.064449417
1.406971	0.998373982
1.278631	0.991967342
1.113159	0.952936146
1.047259	1.196063261
1.243806	0.901464293
0.883406	1.082838098
1.021046	0.977339551
0.755314	0.982914578
1.017431	0.946601608
0.79339	1.074482558
0.9169	0.911804867
1.075643	0.868327997
1.009163	0.858516682
1.006844	0.82053777
1.016155	0.780468568
1.091542	0.808957491
1.109756	0.910589906
0.894045	1.03017633
0.829829	0.804961602
0.725906	0.81084947
0.995107	0.833838403
0.785462	0.849889201
0.924752	0.792656694
0.923124	0.767034084
0.870268	0.743186965
0.793441	0.672520914
0.7799	0.6984352
0.906101	0.665183947
0.905511	0.860990642
0.942099	1.005965785
0.905031	0.84164238
0.821041	0.916704784

0.895766	1.004923189
0.709684	0.915983876
0.700479	1.693809043
0.557088	1.268660723
0.647154	1.245868617
0.619627	0.98167395
0.632172	1.366905597
0.557747	1.370031908
0.844738	1.649036845
0.792751	1.32456542
0.718336	1.42175906
0.628955	1.566297696
0.578598	1.051118448
0.656121	1.049289345
1.068092	0.968576723
1.032611	1.429591327
0.902627	1.299628466
0.860623	1.206057016
0.996712	1.664243177
1.270075	1.00138506
0.836148	1.23180408
1.036048	1.194974855
1.08672	1.394988266
0.768746	1.578540632
0.941665	0.727131947
0.779162	2.45383178
1.19424	1.109073834
1.010715	1.502415177
0.966946	1.241051513
1.339531	1.639816497
1.293075	1.232600746
1.207728	1.856420601
1.165981	1.432629047
1.313845	1.407928014
1.446049	1.266515878
1.210472	1.277339555
1.30542	0.914353203
1.543201	0.954427602
1.578178	0.72352434
1.277448	0.748901633
1.529323	0.405856609
1.369804	0.851791632
1.06805	0.701247719

1.389276	0.741521793
1.563589	0.468529744
1.452684	0.771310616
1.174744	0.855667779
1.161898	1.309608688
1.445672	1.069504762
1.509682	1.07376545
0.951092	1.10960778
1.118434	0.960630614
0.883185	0.922737049
1.314067	1.20263434
1.249304	1.21254105
0.957979	1.01939019
0.955268	1.238769897
0.993901	0.773503167
0.978392	1.074348288
1.184786	1.213922777
1.209561	1.249897348
0.970669	0.875846515
1.552791	1.367462114
1.153739	0.922709361
0.906476	1.318503226
0.724256	0.824106585
1.293192	1.123207836
1.879729	1.124689591
1.628592	1.062448387
1.294902	1.009835501
1.56119	0.987784589
1.378842	1.120778759
1.326766	0.996840755
1.494229	1.167460653
1.268673	0.991984167
1.127566	1.465765647
1.567962	1.020220926
1.220424	1.461650683
1.32231	0.907194595
1.504275	1.387365708
1.188394	1.392454513
1.254064	0.804421242
0.72384	0.918467407
0.848201	1.113380822
0.893914	1.178169407
0.757087	0.604610317

1.557893	1.128184936
1.433187	0.876163982
1.168742	1.080687482
1.041451	1.004664023
1.088808	1.044024812
1.30006	0.674005826
0.928692	0.892817868
1.386727	0.673859545
1.234598	1.216060875
1.401123	0.628639452
1.242866	0.883907392
	0.764524846

Table C.4: Walking Speeds – Sample Calculation

	x	*y*	*frame*	*xChange*	*yChange*	*Frame Distance*	*Inst.Speed*	*Total Distance*	*Avg. Speed*
#	b	s							
0:09:02:64	-2.55	-0.67	1	-2.55	-0.67				
0:09:02:68	-2.54	-0.71	2	0.01	-0.04	0.041	1.235	0.041	1.23
0:09:02:71	-2.55	-0.8	3	-0.01	-0.09	0.090	2.713	0.131	1.97
0:09:02:74	-2.54	-0.83	4	0.01	-0.03	0.031	0.947	0.163	1.63
0:09:02:78	-2.54	-0.89	5	0	-0.06	0.06	1.798	0.223	1.67
0:09:02:81	-2.54	-0.95	6	0	-0.06	0.06	1.798	0.283	1.69
0:09:02:84	-2.52	-1	7	0.02	-0.05	0.053	1.613	0.337	1.68
0:09:02:88	-2.52	-1.06	8	0	-0.06	0.06	1.798	0.397	1.70
0:09:02:91	-2.5	-1.1	9	0.02	-0.04	0.044	1.340	0.441	1.65
0:09:02:94	-2.5	-1.16	10	0	-0.06	0.06	1.798	0.501	1.67
0:09:02:98	-2.48	-1.2	11	0.02	-0.04	0.044	1.340	0.546	1.63
0:09:03:01	-2.47	-1.24	12	0.01	-0.04	0.041	1.235	0.587	1.60
0:09:03:04	-2.45	-1.28	13	0.02	-0.04	0.044	1.340	0.632	1.58
0:09:03:08	-2.45	-1.34	14	0	-0.06	0.06	1.798	0.692	1.59
0:09:03:11	-2.45	-1.4	15	0	-0.06	0.06	1.798	0.752	1.61

0:09:03:14	-2.43	-1.44	16	0.02	-0.04	0.044	1.340	0.797	1.59
0:09:03:18	-2.45	-1.5	17	-0.02	-0.06	0.063	1.895	0.860	1.61
0:09:03:21	-2.43	-1.57	18	0.02	-0.07	0.072	2.181	0.933	1.64
0:09:03:24	-2.42	-1.63	19	0.01	-0.06	0.060	1.823	0.994	1.65
0:09:03:28	-2.41	-1.69	20	0.01	-0.06	0.060	1.823	1.055	1.66
0:09:03:31	-2.41	-1.74	21	0	-0.05	0.05	1.498	1.105	1.65
0:09:03:34	-2.41	-1.82	22	0	-0.08	0.08	2.397	1.185	1.69
0:09:03:38	-2.4	-1.88	23	0.01	-0.06	0.06	1.823	1.245	1.69
0:09:03:41	-2.37	-1.92	24	0.03	-0.04	0.05	1.498	1.295	1.68

Appendix D: Minitab Statistical Analysis Reports

Two-Sample T-Test and CI: 10 Mins Late (1st Train), 10 Mins Late (2nd Train)

Method

μ_1: mean of 10 Mins Late (1st Train)
μ_2: mean of 10 Mins Late (2nd Train)
Difference: $\mu_1 - \mu_2$

Equal variances are not assumed for this analysis.

Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
10 Mins Late (1st Train)	57	1.110	0.277	0.037
10 Mins Late (2nd Train)	62	1.156	0.251	0.032

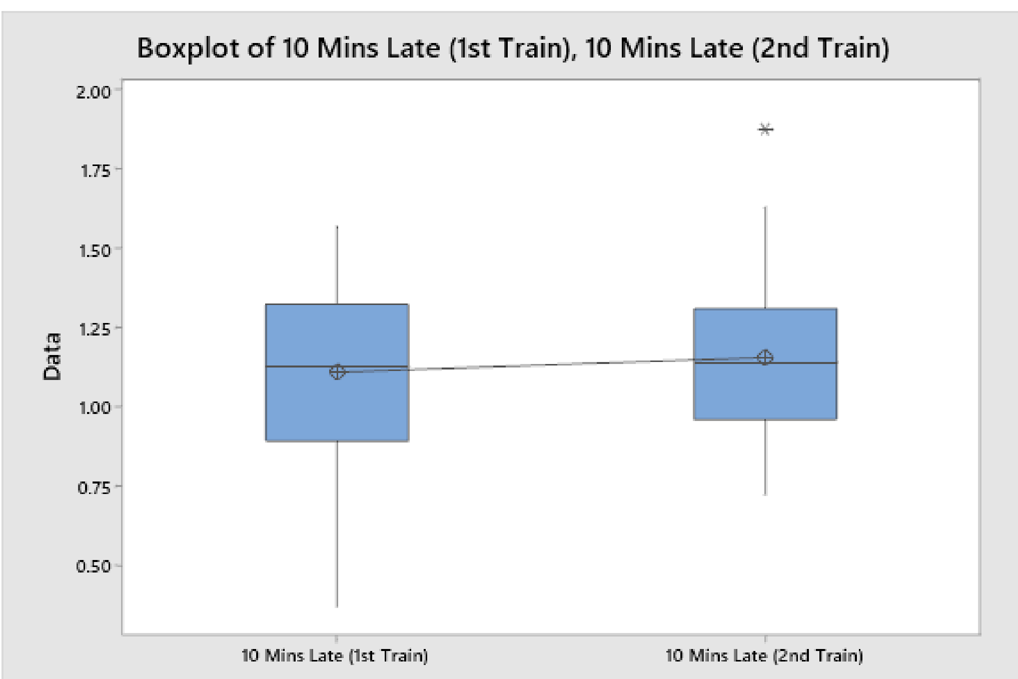
Estimation for Difference

Difference	95% CI for Difference
-0.0462	(-0.1426, 0.0502)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$
Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
-0.95	113	0.344



Two-Sample T-Test and CI: 10 Mins Late (Both Trains), 30 Mins Late

Method

μ_1: mean of 10 Mins Late (Both Trains)
μ_2: mean of 30 Mins Late
Difference: $\mu_1 - \mu_2$

Equal variances are not assumed for this analysis.

Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
10 Mins Late (Both Trains)	119	1.134	0.264	0.024
30 Mins Late	28	1.276	0.199	0.038

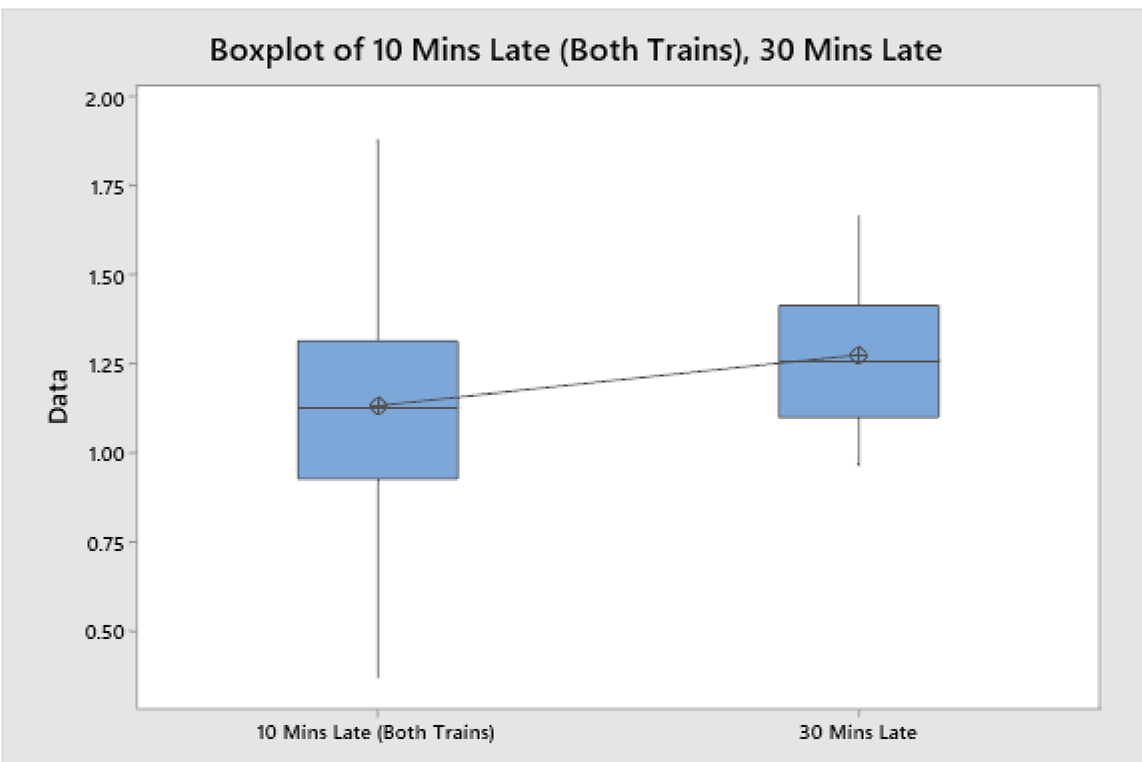
Estimation for Difference

Difference	95% CI for Difference
-0.1414	(-0.2311, -0.0517)

Test

Null hypothesis H₀: $\mu_1 - \mu_2 = 0$
Alternative hypothesis H₁: $\mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
-3.16	51	0.003



Two-Sample T-Test and CI: 10 Mins Late (Both Trains), 50 Mins Late

Method

μ_1: mean of 10 Mins Late (Both Trains)
μ_2: mean of 50 Mins Late
Difference: $\mu_1 - \mu_2$

Equal variances are not assumed for this analysis.

Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
10 Mins Late (Both Trains)	119	1.134	0.264	0.024
50 Mins Late	47	1.182	0.260	0.038

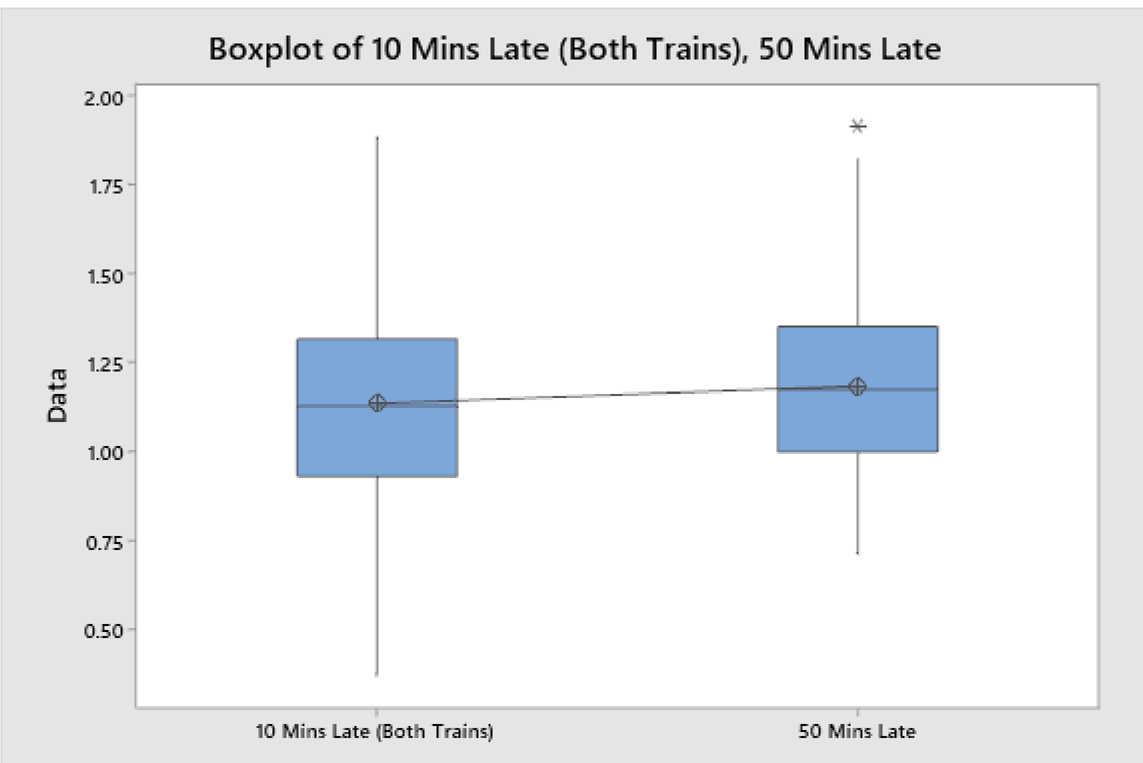
Estimation for Difference

Difference	95% CI for Difference
-0.0475	(-0.1370, 0.0420)

Test

Null hypothesis H₀: $\mu_1 - \mu_2 = 0$
Alternative hypothesis H₁: $\mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
-1.06	85	0.294



Two-Sample T-Test and CI: Queueing, Late to Gate

Method

μ_1: mean of Queueing
μ_2: mean of Late to Gate
Difference: $\mu_1 - \mu_2$

Equal variances are not assumed for this analysis.

Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
Queueing	113	0.860	0.176	0.017
Late to Gate	49	1.503	0.555	0.079

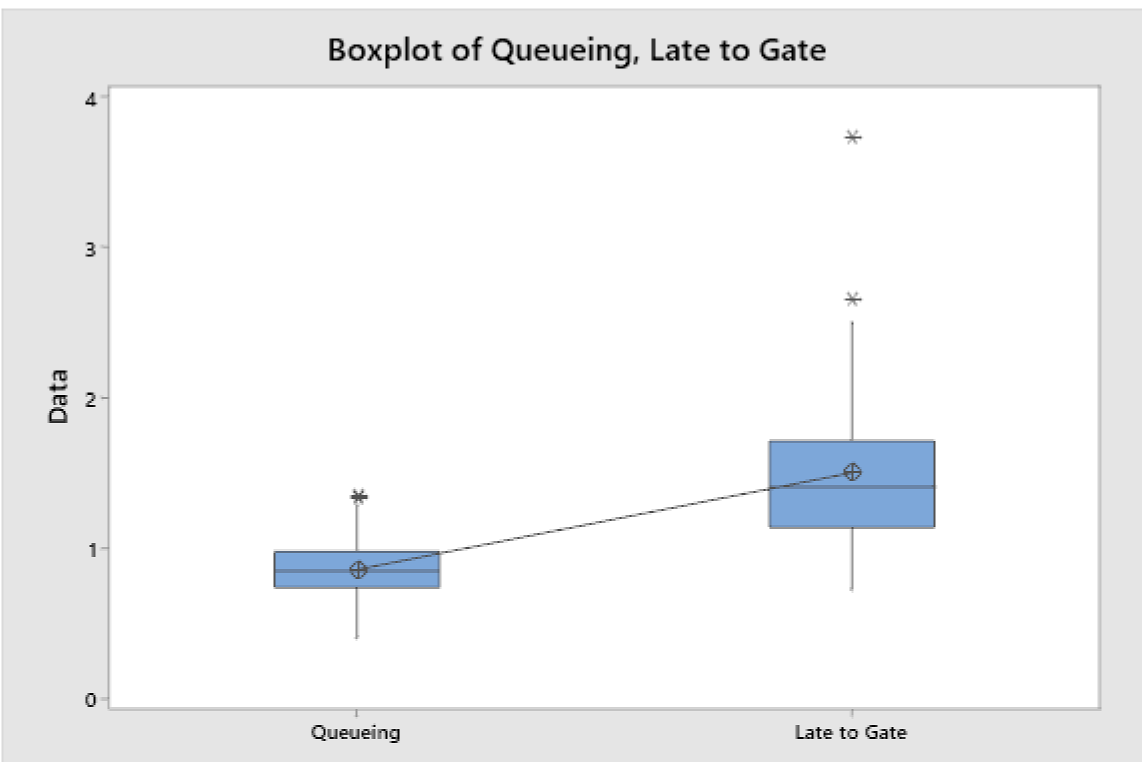
Estimation for Difference

Difference	95% CI for Difference
-0.6437	(-0.8063, -0.4811)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$
Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
-7.95	52	0.000



Two-Sample T-Test and CI: No Factor, Suitcase

Method

μ_1: mean of No Factor
μ_2: mean of Suitcase
Difference: $\mu_1 - \mu_2$

Equal variances are not assumed for this analysis.

Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
No Factor	161	1.180	0.410	0.032
Suitcase	162	1.084	0.302	0.024

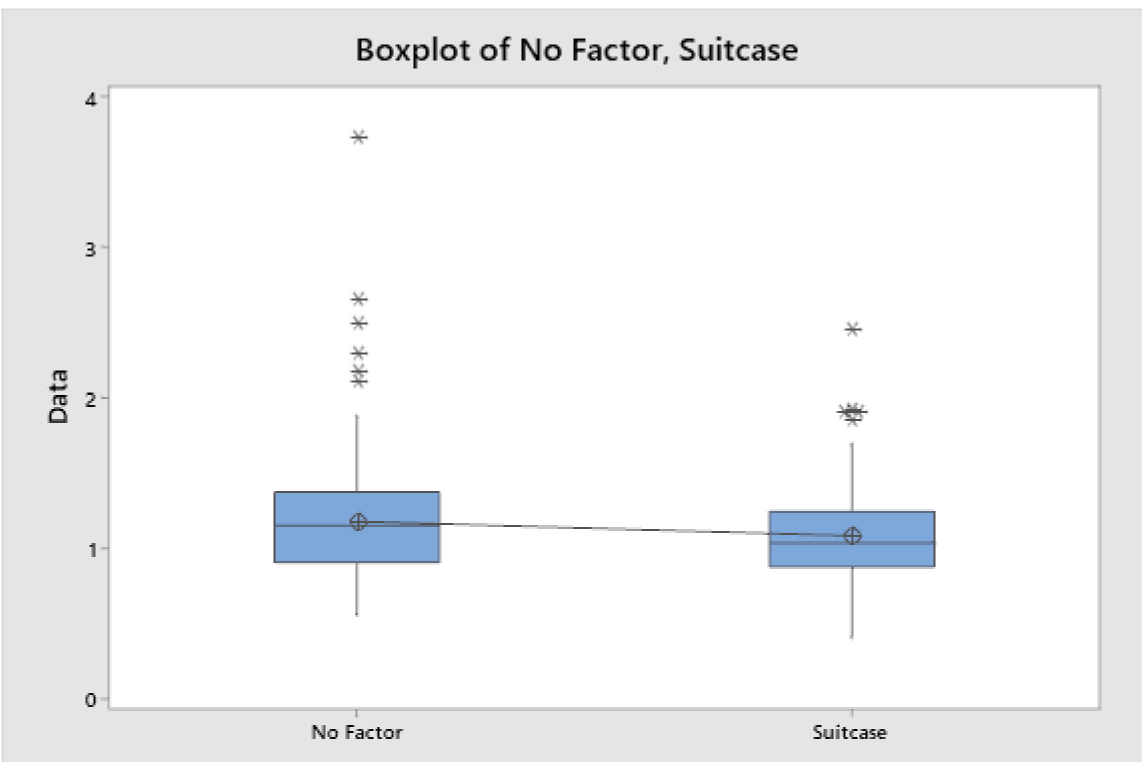
Estimation for Difference

Difference	95% CI for Difference
0.0953	(0.0164, 0.1742)

Test

Null hypothesis H_0: $\mu_1 - \mu_2 = 0$
Alternative hypothesis H_1: $\mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
2.38	294	0.018



Two-Sample T-Test and CI: No Factor, Phone

Method

μ₁: mean of No Factor
μ₂: mean of Phone
Difference: μ₁ - μ₂

Equal variances are not assumed for this analysis.

Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
No Factor	161	1.180	0.410	0.032
Phone	20	1.085	0.236	0.053

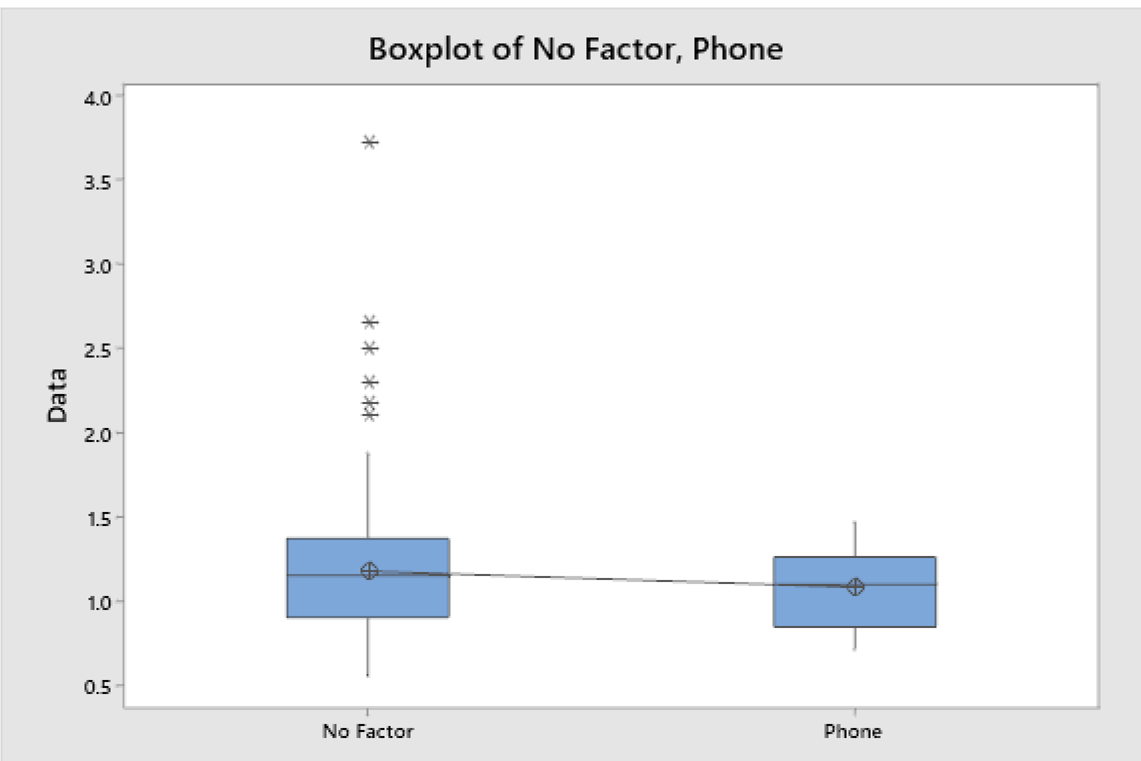
Estimation for Difference

Difference	95% CI for Difference
0.0950	(-0.0307, 0.2208)

Test

Null hypothesis H₀: $\mu_1 - \mu_2 = 0$
Alternative hypothesis H₁: $\mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
1.53	35	0.134



Two-Sample T-Test and CI: No Factor, Family

Method

μ_1: mean of No Factor
μ_2: mean of Family
Difference: $\mu_1 - \mu_2$

Equal variances are not assumed for this analysis.

Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
No Factor	161	1.180	0.410	0.032
Family	16	1.073	0.335	0.084

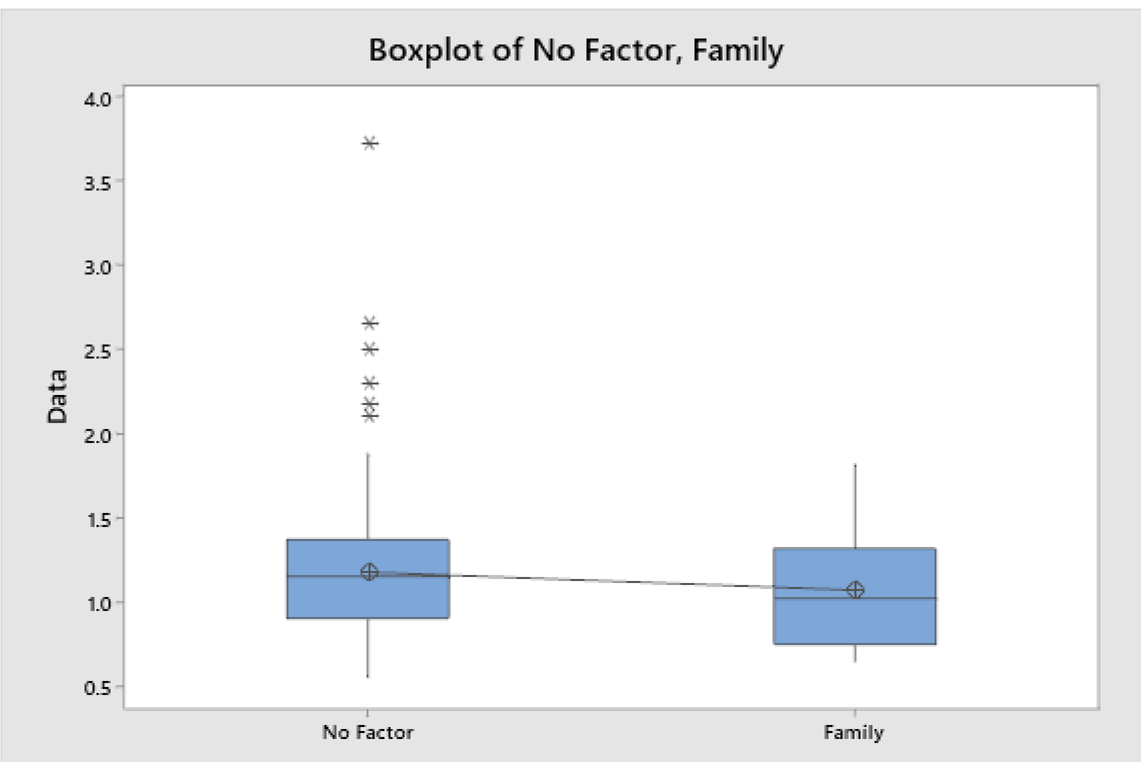
Estimation for Difference

Difference	95% CI for Difference
0.1066	(-0.0814, 0.2947)

Test

Null hypothesis H_0: $\mu_1 - \mu_2 = 0$
Alternative hypothesis H_1: $\mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
1.19	19	0.250



Two-Sample T-Test and CI: No Factor, Mobility Aid

Method

μ_1: mean of No Factor
μ_2: mean of Mobility Aid
Difference: $\mu_1 - \mu_2$

Equal variances are not assumed for this analysis.

Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
No Factor	161	1.180	0.410	0.032
Mobility Aid	6	0.6907	0.0815	0.033

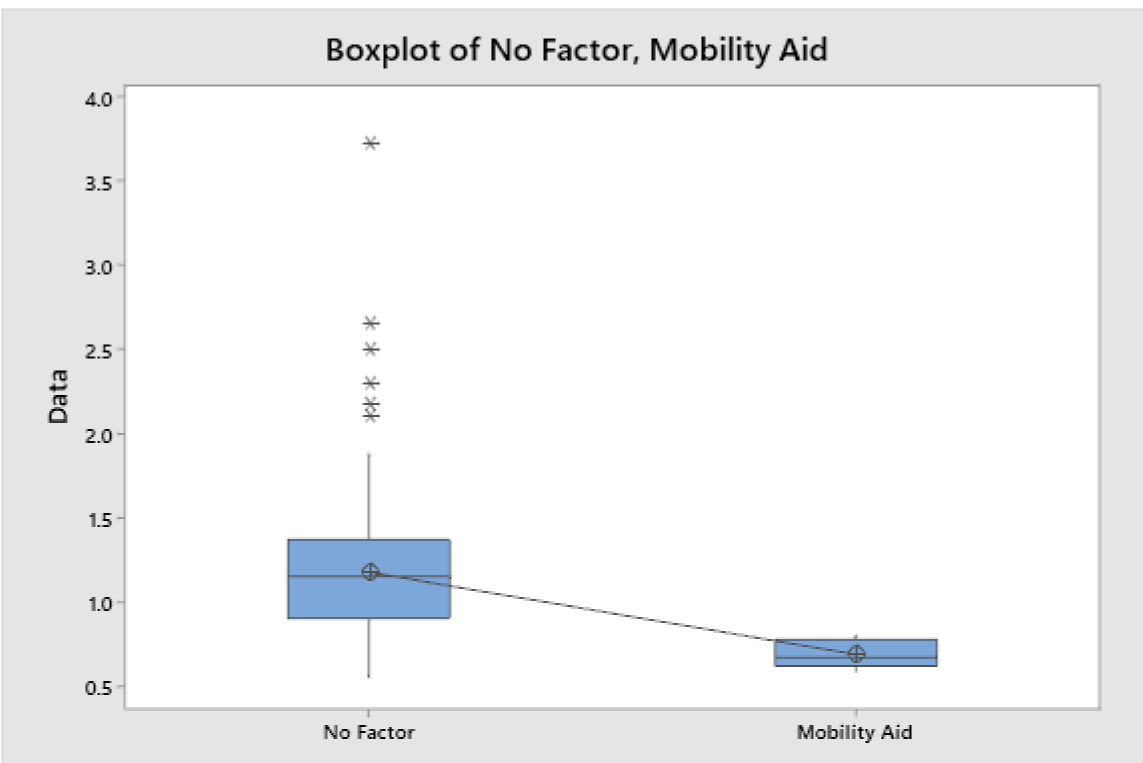
Estimation for Difference

Difference	95% CI for Difference
0.4889	(0.3915, 0.5863)

Test

Null hypothesis H_0: $\mu_1 - \mu_2 = 0$
Alternative hypothesis H_1: $\mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
10.55	18	0.000



Two-Sample T-Test and CI: No Factor, Mobility Impairment

Method

μ_1: mean of No Factor
μ_2: mean of Mobility Impairment
Difference: $\mu_1 - \mu_2$

Equal variances are not assumed for this analysis.

Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
No Factor	161	1.180	0.410	0.032
Mobility Impairment	2	0.520	0.210	0.15

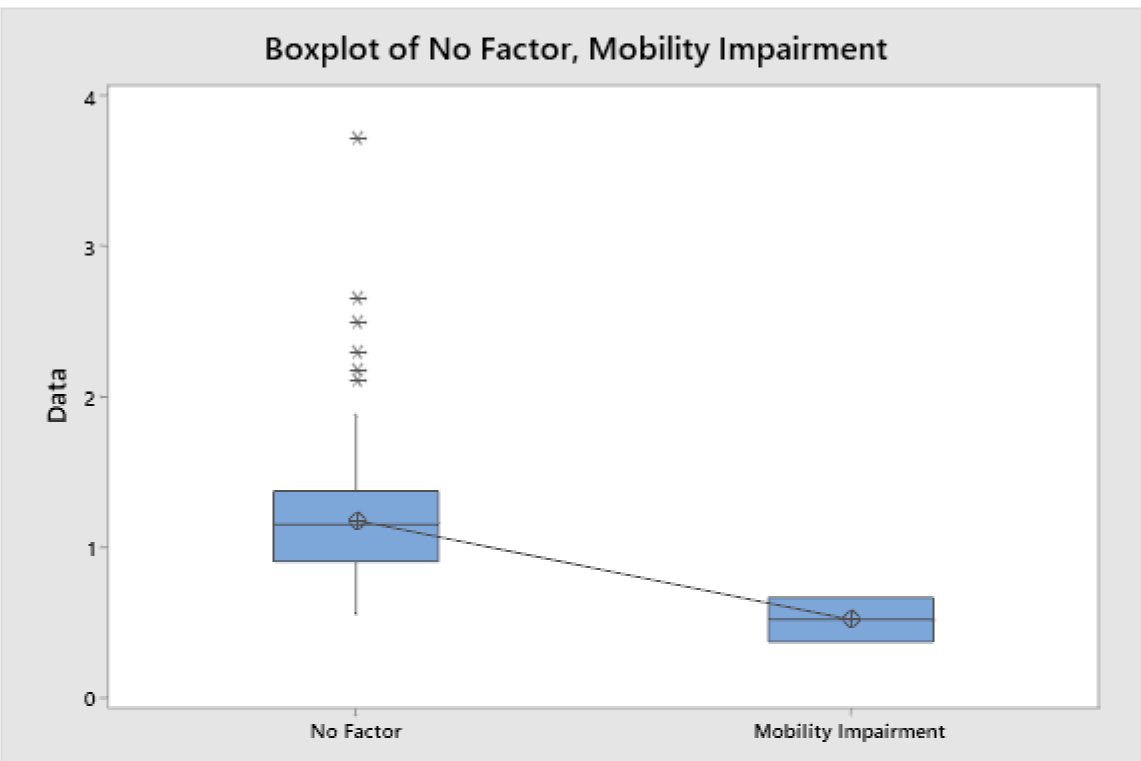
Estimation for Difference

Difference	95% CI for Difference
0.659	(-1.270, 2.588)

Test

Null hypothesis H_0: $\mu_1 - \mu_2 = 0$
Alternative hypothesis H_1: $\mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
4.34	1	0.144



Appendix E: Emergency Egress For The Elderly In Care Home Fire Situations

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EMERGENCY EGRESS FOR THE ELDERLY IN CARE HOME FIRE SITUATIONS

Abstract

Practitioners are continuing to develop egress modelling software for the design of the built environment. These models require data about human behaviour and factors for calibration, validation, and verification. This study aims to address the specific data and knowledge gap: emergency egress of the elderly. Such data is difficult to collect given privacy and consent concerns, with strong relationships generally being required between residences and researchers. Through the observation of nine fire drills at six Canadian long term care and retirement homes, specific evacuation actions and behaviour were observed for 37 staff members and information about the evacuation of 56 residents was collected. These drills demonstrated that emergency egress in long term care and retirement homes is highly staff dependent with 72% of residents recorded requiring full assistance at all stages of movement in evacuation, and that the type of announced/unannounced drill and level of resident care will affect the type of data collected. The development of travel speed and pre-movement is discussed subject to limitation with qualitative

behavioural insights of residents that were observed. This study provides valuable methodological discussion on how to conduct behavioural studies in similar highly restricted research environments. Specific attention is given to understanding the considerations that must be made when using fire drills as data sources, and the impact that these can have on using such data for modelling. This study may inform the initial setup and programming of evacuation models from an actions and behavioural perspectives of staff members and residents.

Keywords: Fire drills, Aging Populations, Dependent behaviour, Evacuation, Behavioural data, Movement time

E.1 Introduction

A demographic factor that has potential to have significant impact on the time required for emergency egress is that the global population is aging.[1] In Canada, the 2016 census showed that seniors outnumbered children for the first time in the country's history.[2] By 2036, seniors are projected to comprise 23%-25% of Canada's population.[3] This change will affect the requirements of the built environment. Aging and elderly populations require more time and assistance to evacuate in emergencies due to the increased prevalence of physical and mental disabilities.[4,5] The Society of Fire Protection Engineers (SFPE) identified the collection of data relating to demographics, specifically vulnerable populations, as the priority theme in its 2018 Research Roadmap.[6] This demonstrates that there is a need for understanding of the behaviour, actions and dependencies of vulnerable populations, such as the elderly, in fire events.

In places such as long term care (LTC) and retirement homes, which specifically cater to this demographic, the role played by care staff can have a substantial impact on the nature of the evacuation process.[7] This can be seen in a number of prominent and deadly fires in LTC and retirement-type homes. Devastating fires (ex. Rosepark Care Home in Scotland in 2004 and in the

L'Isle-Verte Senior's Residence in Canada in 2014) have resulted in significant loss of life.[8,9] There have been eight fires in Canadian residences dedicated to the care of the elderly within the last nine years alone with life loss (Table E.1).

Table E.1: Recent Fires in Canadian Long Term Care, Retirement and Seniors Homes [30-39]

Date	*Place*	*Location*	*Fatalities*
Mar-18	R J Brooks Living Centre	Bancroft, Ontario	1
Sep-17	Extendicare Port Hope Long Term Care Centre	Port Hope, Ontario	0
Jul-17	Oasis Residence	Terrebonne, Quebec	1
Nov-16	Domaine des Trembles	Gatineau, Quebec	0
Mar-16	Villa Carital	Vancouver, British Columbia	0
Dec-15	Medicine Tree Manor	High River, Alberta	0
Jun-14	Extendicare Starwood	Ottawa, Ontario	0
Jan-14	L'Isle-Verte Seniors Residence	L'Isle-Verte, Quebec	32
Aug-12	Retirement Home	Edmonton, Alberta	1
May-12	Place Mont-Roc home	Hawkesbury, Ontario	2
Apr-12	Long Term Care Home	Langley, British Columbia	1
Apr-11	Rainbow Suites Retirement Home	Timmins, Ontario	1
Apr-10	St. Joseph's Residence	Winnipeg, Manitoba	0
Jan-09	Muskoka Heights Retirement Home	Orillia, Ontario	4

In order to be representative of real-life emergency situations that can inform building design, egress models must represent various elements of human behaviour and take into account the wide range of factors that can influence how and when people will evacuate in diverse situations and environments. These models require calibration, validation and verification. They rely upon access to data covering a range of populations and environments. Data of this nature can come from a variety of settings, can include a wide spectrum of demographics, and can represent varying levels of credibility for using and developing egress models and subsequent design. Herein, qualitative and quantitative behavioural data was collected through the observation of nine fire drills at six different LTC and retirement homes in Ontario, Canada. Given the high dependence of residents on staff members in these homes, the study focuses on the actions and behaviours of the staff members and their interactions with residents during fire drills. The paper highlights the nuances of conducting fire drills in LTC and retirement homes and the complexities of collecting data from such drills. The paper details the process that was followed to build relationships with LTC and retirement homes, to observe and collect data from fire drills at these homes. Additionally, this study discusses the limitations to be considered when using fire drills as a data collection method. The methodology herein tailors to how similar and future studies by other researchers and practitioners may be conducted within restricted research environments. The study is Canadian focused but certain conclusions and material will extend to broader use. While the datasets are subject to various limitations noted herein, practitioners may find this study useful to inform the initial setup and programming of their evacuation models from an actions and behavioural perspective of staff members and residents. This manuscript is the first in a series by the authors which is intended to be followed by a modelling verification and validation study which is beyond this current manuscript's scope.

E.2 Theory

E.2.1 Legal Fire Drill Requirements

In this study, the observed retirement homes had three levels of care. These levels range from independent, assisted and memory care. In independent care, there is little to no supervisory staff needed for residents. Assisted care offers staff assistance with day-to-day activities. Memory care assistance offers extended care for residents with neuro-diverse requirements such as early stage dementia or derivatives. These residents often have difficulty with recognition and can easily be confused. For their safety, these residents receiving memory care assistance are located on a secured floor, with staff assistance available. LTC home residents tend to require physical or cognitive assistance and have restricted mobility. Enhanced monitoring and care is provided with 24-hour nursing.

The two types of care homes are both required to have fire safety training and procedures per the National Fire and Building Code of Canada (NBC and NFC herein) in addition to the provincial codes.[10,11] The procedure of a fire drill is the responsibility of the building management.[12] The procedure should address the potential building fire hazards with respect to the residing occupants, note building safety features, indicate the target number for non-staff occupant participation during the drill and the number of trained staff involved. Procedure should follow the fire department regulations and confirm that the emergency systems comply with the NBC.12 The NFC also addresses that the frequency of the fire drills depends on the occupancy type. For elderly care homes, the staff are required to participate in a fire drill once a month and the staff participation must be recorded. In LTC homes, three fire drills are required every month, one on every shift (morning, afternoon, night).[11,13] Both LTC and retirement homes are required to have one fire drill per year observed by a city fire marshal. This drill must represent the worst-case timing scenario - the least number of staff that would be present in the home - the night shift. It also requires that all residents in the fire drill wing be evacuated to a place of relative safety e.g. to an adjacent fire compartment, and not necessarily to outside the building. The code allows staff members to stand in and act in the place of residents.[11,13]

E.2.2 The Role and Purpose of Fire Drills

A drill can be defined as "an exercise involving a credible simulated emergency that requires personnel to perform emergency response operations for the purpose of evaluating the effectiveness of the training and education programs and the competence of personnel in performing required response duties and functions".[14] Drills are often used to evaluate the performance of individuals in a simulated emergency environment so as to gauge how they could perform during a realistic emergency. Drills can also be seen as training and educational activities to teach people how they should act in an emergency situation.[12] In both cases, drills provide the opportunity to address performance, be it an individual act, role or procedure, or the interactions between different groups, individuals, environments, and emergency scenarios. Drills can also provide opportunities to gather valuable information about evacuee behaviour and procedural design.[15] Given that conducting "experiments" in the traditional sense of the word is generally not possible for ethical and safety concerns – particularly with vulnerable populations – drills, along with other models, can provide a limited opportunity to better understand aging populations' behaviour in fire. Egress drills are commonly used tools. However, their benefit, effectiveness and limitations are not widely understood as discussed in depth elsewhere.[12] This is a critical consideration when using drills as a means of data collection for research. It is important to understand that drills are a simulation, a model of an emergency situation. Practicality, safety, cost and ethics can limit their value.[12] Researcher influence can also impact the realism of a drill and the quality of the data collected and should therefore be managed carefully to minimize its impact.[16] For the modeller using this data it is critical to know the limitation and applicability of the data to keep it within context and understand its impact on the practitioner's uncertainty.

E.2.3 Egress Data and Evacuation Modelling

Over the past few decades, evacuation modelling software has been developed for applications in crowd dynamics, pedestrian movement and evacuation processes.[17] These models are used by various fields and disciplines, and as such they play an important role in understanding and representing human movement and evacuation behaviour. There exist many different egress models, ranging from hydraulic calculations to adaptive agent-based approaches.[18] These models vary in the way that they configure buildings, populations, and procedures.[19] Practitioners have reviewed and summarized the features and capabilities of current egress modelling software.[20,21]

Models rely on an understanding of the situation being simulated and appropriate data input. This data is not only used for creating egress model simulations, it is also necessary for the verification and validation of the tools themselves.[22] Data can come from a variety of sources including simulated emergency evacuations such as fire drills. Much of the data available in publicly accessible literature has been compiled and can be found in the fifth edition SFPE Handbook.[23] An understanding of human behaviour in fire and the dependencies between groups and their care takers are important when using and interpreting the data available. Additionally, data collection context, techniques and processes can have a large impact on the nature of the data collected and therefore need to be considered when looking to use the data in a computer model specifically when dependent behaviour is sought to be understood.

E.3 Methodology

Data relating to fire drills and procedures was collected in collaboration with three LTC homes and three retirement homes. The characterization of the buildings used for the nine drills is summarized in Table E.2 and E.3. The drills are numbered in the order that they were observed. Early research focused on LTC homes (Drills 1-4, 6) while the more recent studies focused on retirement homes (Drills 5, 7-9). The first four drills were monthly drills in which resident participation was not mandatory while the latter five drills were legally required annual fire marshal-observed drills. In total, six different homes agreed to have drills observed by researchers, and nine individual drills were observed (three drills at one home, two at another, and one drill at each of the other four homes).

Semi-structured, formal conversations were had with a staff member responsible for organizing fire drills and training staff at each of the participating homes. Monthly or annual fire drills were observed in person with notes being taken by hand during the drill. Sections 3.1 and 3.2 detail the methodology for the data collection.

Table E.2: Summary of participating long term care and retirement home locations where data was collected

	Drill 1 [a]	*Drill 2*	*Drill 3* [a]	*Drill 4*	*Drill 5* [b]	*Drill 6* [a]	*Drill 7* [b]	*Drill 8*	*Drill 9*
Number of Storeys	3	7	3	2	5	3	5	5	6
Number of Residents	161	193	180	192	127	190	125	N/A [c]	N/A [c]
Long Term Care Home	X	X	X	X	-	X	-	-	-
Retirement Home	-	-	-	-	X	-	X	X	X

[a] Drills 1, 3 and 6 were observed in different wings at the same location at the same level of care but at different dates so occupancy differs.

[b] Drills 5 and 7 was observed at the same location at different levels of care location at the same level of care but at different dates so occupancy differs. [C] Exact occupancy not available but > 100.

E.3.1 Building Connections and Conducting Conversations

The first stage of the research involved building a relationship of trust with LTC and retirement homes. Convenience sampling was used for the study, with as many homes in study region being contacted as possible (based on the information that was available online). Four rounds of written requests were sent out to managerial staff at the homes describing the project and inquiring about their willingness to talk about the home's fire safety practices, policies and evacuation procedures. It was made clear that the authors would answer questions or discuss any concerns that the home representatives had prior to agreeing to a meeting. Table E.3 details the response rate for each round of meeting requests. Formal conversations were had in person at the homes with the head staff member responsible for organizing and overseeing fire drills and fire safety training and responses were written down by the researcher (general information, not exact quotes). The pre-determined questions focused on general building information, fire detection systems, active and passive systems, fire strategies and staff procedures, resident level of care as well as general demographics and resident population characteristics.

Table E.3: Response rate for each round of meeting requests

Round of Meeting Email Requests	*Request Timeframe*	*Type of Home*	*Number of Homes Contacted*	*Number of Homes that Responded*	*Number of Homes that Agreed to Participate*	*Number of Homes Where Meetings Were Conducted*	*Number of Homes Where Drills Were Observed*
1	Sept. 2014	Long Term Care	8	4	3	2	1
2	Sept. 2015	Long Term Care	7	4	4	4	3
3	Jan. 2016	Retirement	7	2	1	1	1
4	May 2017	Retirement	15	6	4	3	3

In total, meetings were conducted at seven different LTC and retirement homes. One LTC home where a meeting was conducted could not be reached to arrange a fire drill observation. At homes where multiple drills were observed, follow-up conversations were had prior to observing subsequent drills so as to update any information that had changed since the previous meeting.

E.3.2 Fire Drill Observation and Data Collection

Following the meetings, the participating homes were asked if they would be willing to allow members of the research team to observe one of the homes' required fire drills as part of this research study; six different homes agreed. The authors were invited to observe drills that were pre-arranged by the different homes based on monthly or yearly fire drill requirements. Information such as floorplans, staff fire safety procedures and anticipated number of participants were acquired in advance of each drill and were used to prepare a guide which was given to each observer.

The method of observing each fire drill followed a similar process so as to maintain compatibility and allow for comparisons to be made. Each drill was observed in person from within the designated fire wing (outside the room compartments). This method of data collection was necessary given that informed consent of residents living with dementia could not practically be obtained for using cameras for data collection. Additionally, filming nursing staff during the fire drills was forbidden as third-party evaluation by film was prohibited by their unions. Research ethics were also more easily obtained in this method of data collection. It is acknowledged by the authors that this method of observation does not allow for all events that may occur during a drill to be recorded and analyzed. While the authors acknowledge this can result in a loss of important data, the willingness of the homes to allow the drills to be observed in the first place was in part due to the fact that cameras were not being used.

At each home, the authors met with the drill coordinator for a pre-drill discussion on the details of the drill. If the drill was a worst-case scenario annual drill, the drill coordinator would also hold a pre-drill discussion with the staff members participating to review procedures, assign roles, and answer questions (participating staff members were briefed for Drills 5 – 9). The drill observations took place within the building wing where the evacuation was taking place. Three to four researchers (led by at least one of the authors, but also including those on their research team) attended each fire drill and were positioned along the corridors of the fire drill area to limit interference with staff procedures. The number of researchers in attendance at each drill was determined based on maximizing the amount and quality of data collected, and by minimizing the impact of the observers on the drill (based largely on the geometry of the floorplan – hallway length, linear vs. non-linear layout – and whether an observer could remain in the same location throughout the course of the drill while being able to record the necessary data). For the first four drills which took place at LTC homes, each observer was responsible for recording general observations of participating staff and residents along with the corresponding times. For Drills 5 – 9, the timestamps of specific actions, including when staff members entered the wing and when residents or staff entered a room, left a room, and entered the safe zone, were the focus of the observation. Behaviours exhibited and actions undertaken by both staff and residents were also noted, along with the times that they were observed. Written notes were kept during the drill and synchronized stopwatches were used by observers to note key timestamps. For these later drills, the observation task distribution between the researchers depended on several factors including the geometry of the building wing being evacuated, the level of care being provided (and corresponding level of resident dependency), and the number of participating staff and residents. For Drills 5, 6 and 9, each researcher recorded the actions of one staff member. This was deemed the most effective method given that the residents in Drill 5 and 6 had a high dependency on staff (memory care floor or long term care home) and would therefore not evacuate on their own, and for Drill 9 there were only a few residents living on the evacuation floor. It should be noted that in contrast to Drills 5 and 9 where the number of observers equalled the number of participating staff members (3:3), there were more staff participating in Drill 6 than there were observers (8:3). It was determined that in order to collect data to the degree of specificity required while not unduly interfering with the drill by having too many observers present, it was necessary to focus closely on a select number of staff. Therefore, each researcher observed one staff member. This meant that the same amount of data was collected as in the other drills, but the proportion of data collected to potential data was smaller. For Drills 7 and 8, researchers focused on recording actions observed in specific sections of the wing. This was deemed the most effective method as the drills took place on floors where residents were more independent and autonomous and therefore were expected to evacuate without extensive staff assistance. This method allowed the researchers to observe and record the actions of both the staff and the residents (both autonomous and non, herein we define autonomous as residents who left their room on their own ability and moved to the safe zone on their own ability, with or without prompting, with or without walkers, wheel chairs etc). Given the floorplan geometry, this method also allowed the researchers to remain in one place throughout the drill, limiting their impact on the drill. Following each drill, the researchers observed the post-drill discussion held by the drill coordinator with the participating staff (and the fire marshals if present). After leaving the homes, the researchers then met to discuss the drill and to consolidate the raw data each person had collected. Table E.4 details the conditions of each drill including the number of participating staff and residents, the working shift during which the drills took place, and the duration of the drill. Table E.5 shows the frequency and probability of observed staff actions and behaviours during the drills, and Table E.6 shows preevacuation times and percent evacuation times for 5 of the observed drills. These tables will be discussed in later sections of the paper.

Table E.4: Summary of fire drill conditions

	Drill 1	*Drill 2*	*Drill 3*	*Drill 4*	*Drill 5*	*Drill 6*	*Drill 7*	*Drill 8*	*Drill 9*
Type of Drill Observed	Monthly	Monthly	Monthly	Monthly	Annual	Annual	Annual	Annual	Annual
Working Shift	Day	Evening	Evening	Evening	Night	Night	Night	Night	Night
Time of Drill	2:00 pm	3:30 pm	3:00 pm	3:30 pm	3:30 pm	10:00 am	1:30 pm	2:00 pm	10:30 am
Number of Staff	15	7	9	7	3	8[a]	3[b]	3	3
Number of Staff Stand-Ins	0	0	0	0	3	11[c]	1	0	4
Number of residents participating	3	0	2	2	10	14	22	14	6
Number of residents that did not evacuate	0	1	0	0	0	0	0	4	0
Number of residents recorded	3	0	2	2	10	5	18	10	6
Autonomous residents recorded[e]	3	0	0	0	1[d]	0	11	1	0
Drill Timing to "all clear" (mm:ss)	6:00	5:00	4:52	3:23	13:33	9:08	14:28	15:05	7:38

[a] 8 staff participated in the drill, data was collected for 3 of them

[b] 3 staff participated in the drill, data was collected for 2 of them

[c] 11 staff stand-ins participated in the drill, data was collected about 7 of them

[d] Resident evacuated on their own, but were returned to their room and then evacuated by staff

[e] Autonomous is defined as residents who left their room on their own ability and moved to the safe zone on their own ability, with or without prompting, with or without walkers , wheel chairs etc.

Table E.5: Frequency and Probability of Observed Staff Actions and Behaviour

Action or Behaviour	***Overall Frequency From All Nine Drills*** *# of Staff Observed (# of Drills Observed In)*		***Probability Based on Total Number of Actions (%)***	***Probability Based on Total Number of Staff Observed in all Drills (%)***
Pre-Drill Actions				
Normal (unaware of drill about to occur)	23	(3)	9.7%	62.2%
Staged (aware of drill about to occur)	14	(5)	5.9%	37.8%
Perception of Initial Stimulus (Drill Start)				
Ambiguous - Observe behaviour of others	0	(0)	0.0%	0.0%
Unambiguous - Alarm, intercom message, staff radio devices	37	(8)	15.7%	100.0%
Seek and Disseminate Information, Investigate				
Already in fire wing when drill starts	10	(6)	4.2%	27.0%
Travel to and enter wing where the fire is located	27	(7)	11.4%	73.0%
Search for the fire (checking rooms)	10	(2)	4.2%	27.0%
Go right to fire room (do not search other rooms)	6	(6)	2.5%	16.2%
Communicate location with collogues via handheld radios	5	(2)	2.1%	13.5%
Raise the Alarm / emergency message via intercom system	1	(1)	0.4%	2.7%
Seek information from other staff members	5	(3)	2.1%	13.5%
Seek information from fire marshal or drill coordinator	1	(1)	0.4%	2.7%
Initial Securing of Environment				
Bring fire extinguisher into wing	7	(5)	3.0%	18.9%
Locate/entire fire room	14	(7)	5.9%	37.8%
Simulate fighting fire using fire extinguisher	1	(1)	0.4%	2.7%
Place towels under fire room door	2	(2)	0.8%	5.4%
Clear all obstacles out of hallway	8	(1)	3.4%	21.6%
Close resident room doors (pre-evacuation)	2	(1)	0.8%	5.4%
Resident Evacuation				
Check rooms for residents (initial check)	16	(6)	6.8%	43.2%
Assist residents with pre-movement actions (in resident rooms)	3	(2)	1.3%	8.1%
Verbally prompt residents to evacuate (not req.to walk with)	2	(1)	0.8%	5.4%

Guide and walk with residents to safe zone	14	(7)	5.9%	37.8%
Guide/assist resident back into room (still within fire wing)	1	(1)	0.4%	2.7%
Aide another staff member in evacuating a resident	3	(2)	1.3%	8.1%
Close room doors upon exit of room	4	(3)	1.7%	10.8%
Do not close room doors upon exit of room	2	(2)	0.8%	5.4%
Re-Checking Rooms and Marking as Clear				
Use Evacucheck or hanging marker to indicate cleared room	9	(5)	3.8%	24.3%
Re-Check evacuated rooms (once)	5	(2)	2.1%	13.5%
Drill Closure				
Stand around	3	(1)	1.3%	8.1%
Say that all residents have been evacuated, in bed	1	(1)	0.4%	2.7%

Table E.6: Drill Evaluations of Only Recorded Residents

Drill	*Pre-evacuation Times*	*Time which Percentage of People Evacuated [MM:SS]*			
	Avg [Min – Max]	25	50	75	100
5	5:36[0:47-0:16]	4:52	5:37	8:27	11:19
6[a]	2:02[0:46-3:13]	1:19	2:45	2:47	3:38
7	3:09[0:32-10:39]	1:20	3:16	8:14	12:16
8	6:53[2:25-11:42]	5:28	7:10	10:15	13:55
9	3:53[1:29-5:32]	4:37	6:52	7:03	7:32
Average	4:18				

[a] only 5 residents of 14 are recorded.

E.4 Results

E.4.1 Formal Conversation Data

Though each home had different architectural designs and features, the buildings were typically organized in the same way. In the LTC homes, this meant that each floor was compartmentalized into wings or units, which were straight hallways that generally branched off a central core. The elevators were centrally located, and fire rated stairwells were located at the end of each unit. The wings were separated by fire rated doors, creating compartmentalized units. This enabled horizontal evacuation to take place during emergency situations. In the retirement homes, this compartmentalization was only seen if the home had a floor or wing designated for the care of residents with dementia. Most floors of the retirement homes consisted of rooms branching off a main hallway. Horizontal evacuations were still the first stage of an evacuation in the retirement homes, however residents would be evacuated to the stairwells.

In the LTC homes, the average age of residents was 75 to 88 years. Based on their knowledge about the residents, it was estimated by the staff members participating in the initial meetings that between 88-100% of residents would require some form of assistance to evacuate horizontally given the number of residents with cognitive and/or physical disabilities. While the need for assistance was less in the retirement homes, in one building for example, over 90% of the residents would still require assistance to go down the stairs. Staffing levels were consistent among both the LTC and retirement homes - that the least number of staff were present during the night shifts.

The formal conversations provided information on the fire evacuation procedures and practices at each home. Each home had a fire plan that was updated annually and reviewed by the fire department. The official procedures varied from home to home, however they were similar in nature and are published in publicly available policy literature. The REACT fire response procedure (Remove those in danger, Ensure door is closed, Activate alarm, Call 911, Try to extinguish the fire) was used by three homes, with another home using the RACE method (Rescue, Alarm, Contain the fire, Extinguish). The representatives at two homes did not cite a specific reaction acronym, however the approach they described closely resembled the REACT method.

In addition to the initial fire safety training they received as part of their orientation upon being hired, employees were required to participate in annual training and fire drills. During the monthly fire drills, the residents were not required to participate as it was viewed more as a way for the staff to practice the steps that they would need to go through in an actual fire evacuation. In both the LTC and retirement homes, this involved locating and evacuating the fire room (and any connecting rooms) followed by the rooms on either side and the one directly across the hall from the fire room: these occupants are considered most at risk during the initial stages of a fire. This was referred to as the critical triangle (Figure E.1). The rooms were then to be progressively evacuated, starting with those in closest proximity to the fire room. All doors were to be closed after each room was evacuated. Each home had a way of designating which rooms had already been evacuated. Some homes used Evacuchecks which were tabs attached to the doorframe of each room that could be flipped once the room had been checked, other homes hung a tag on the door handle (Figure E.2a and E.2b).

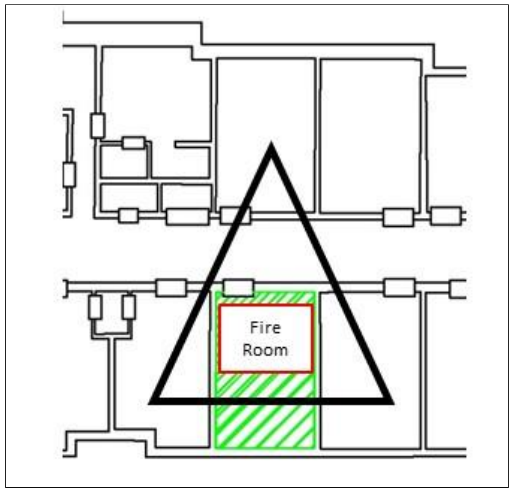


Figure E.1: Visualization of the "critical triangle" that determine what are weighted to be evacuated first.

Figure E.2: (a) Evacucheck before evacuation (b) after evacuation

In the LTC homes, where some residents were bedridden, several different methods of physically assisting residents during real evacuations were described. One home could use mechanical lifts to move bedridden residents into a wheelchair, another home moved the beds themselves into the hallway and into the safe zone. The two other LTC homes used what was known as the blanket method, where bedridden residents were wrapped in their sheets, guided to the floor and then pulled into the safe zone. As the participating retirement homes did not have any bedridden residents given the level of care they provided, such methods were not necessary. Additionally, it was also expressed by the LTC home representatives that while the staff were searching for the fire, they were supposed to close any open resident room doors as well as clear the hallway of all obstacles (wheelchairs, nursing carts, etc.). In the LTC homes, the staff were also expected to make a "Code Red" announcement over the intercom at the start of the drill to inform all staff in the building that a fire had been detected. In contrast, staff at the retirement homes were notified of the fire emergency via handheld radios instead of over the intercom system. During both LTC and retirement home fire drills, one staff member was expected to simulate calling emergency services and one staff member was required to remain on a floor or wing that provided physical and/or cognitive assistance.

It is important to note that not all the actions and procedures discussed above are tested during fire drills. While these actions describe what staff are supposed to do during an actual fire, however, for various reasons discussed in later sections of this paper, not all are expected to be done during the monthly fire drills (they are required for the annual, fire marshal observed drill).

E.4.2 Drill Observations

Sections E.4.2.1 – E.4.2.9 provide summaries of the nine observed drills, where only critical information is provided. The significant times recorded for each observed action and behaviour are written in mm:ss format. The drill floorplans (Figures E.3 – E.11) may show more residents and staff stand-ins than are noted in the description (the location of all participating residents and staff stand-ins were disclosed prior to some of the drills, including those who did not end up participating or were not observed during the drill). Rooms labelled “Room #” represent resident rooms that were or would normally be occupied by a resident (including rooms from which residents were not evacuated during the drill). Rooms labelled “Vacant Room #” indicate rooms where residents were not living at the time. Research observer locations are shown in each drill figure. Table E.4 summarize the parameters for each drill.

E.4.2.1 Drill 1 (Long Term Care Home – Day time working shift)

Fifteen staff members participated in the drill. Three residents participated and evacuated without any assistance from staff. The other residents in the wing either remained in their rooms or had left just before the drill started.

The floorplan of the wing where the drill took place can be seen in Figure E.3. The drill started with the activation of the fire alarm and an announcement over the intercom indicating "Code Red". After 30 seconds, the staff at the nursing center began discussing if they should call emergency services. They were told by another staff member not to as it was "just a drill". At 0:50, one resident evacuated the wing through the main exit instead of the one adjacent to their room. The fire room was located after 1:20 and staff begin to clear the hallway. At 2:20, a staff member was assigned to simulate calling emergency services. Once the hallway was cleared, the staff began checking resident rooms, closing doors and marking the rooms as clear. Two residents from the same room evacuated the wing at 3:39. Ten seconds later, one of those residents returned to their room. Staff announced that the evacuation was complete at 4:15 and “all clear” was announced at 6:00. The post-drill debriefing followed. During the debriefing, staff members discussed their confusion about what they should do during an evacuation (when to call emergency services, which exits to use, what to do at night when they are shortstaffed). The drill coordinator then reviewed the steps according to the home's fire safety plan with the staff.

E.4.2.2 Drill 2 (Long Term Care Home – Evening time working shift)

The second fire drill took place on the evening staffing shift. It was expected that three to four residents would participate, though none did. According to the home's fire safety plan, the residents who were bedridden would be kept in their beds and then moved out of the wing.

However, this was not something that was intended to be simulated during fire drills.

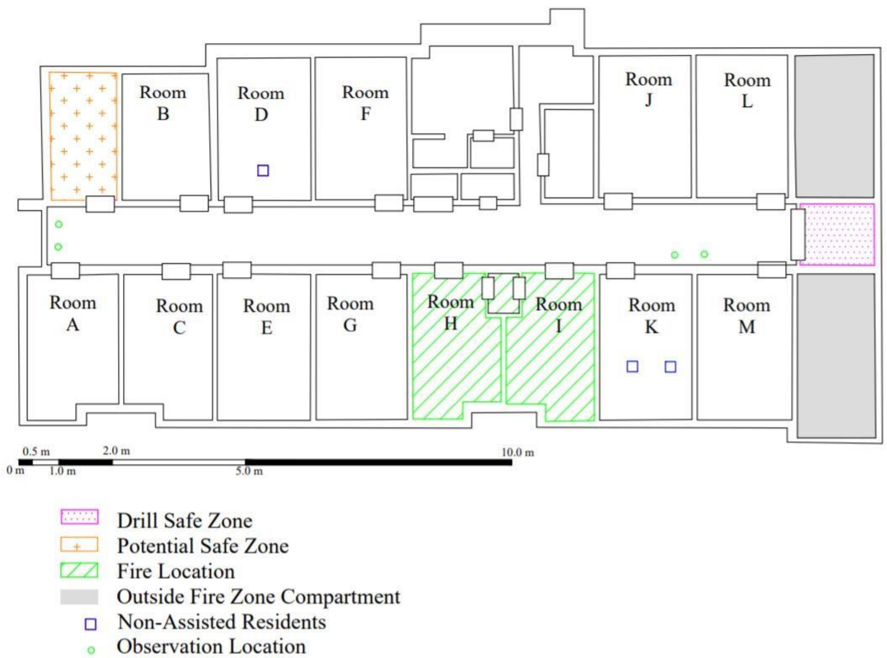


Figure E.3: Drill 1 Floorplan

The floorplan of the evacuated wing can be seen in Figure E.4. The fire alarm indicated the start of the drill, after which "Code Red" was announced over the intercom. The first staff member entered the wing at 0:19 and entered the designated fire room at 0:32. During the 24 seconds that the first staff member was in the fire room, two additional staff entered the wing. Upon leaving the fire room (not closing the door to the room all the way), the first staff member moved back down the hallway. Ten seconds later, a second staff member checked the fire room, leaving 10 seconds later and closing the door. At 2:00, a green checkmark was placed on the fire room door and the door of the room next to it, and a fourth staff member entered the wing. Three additional staff members entered the wing at 2:12, with one asking if the fire room had been checked. At 3:00, one staff member said that all the residents were in bed and another staff member finished checking a room and stood outside the room with the door open (a resident was inside the room). At 3:11, the drill coordinator announced the end of the drill and the staff began to move into the hallway outside of the wing. The post-drill debriefing began soon afterwards, and "all clear" was announced over the intercom at 5:00. A key point that the staff discussed during the post-drill debriefing was that there needed to be a better way for staff within the fire wing to communicate with those outside the wing as there was no way to know how many staff should be sent to assist with the evacuation.

Figure E.4: Drill 2 Floorplan

E.4.2.3 Drill 3 (Long Term Care Home- Evening time working shift)

The floorplan of the wing where the third drill took place can be seen in Figure E.5. The drill coordinator activated the fire alarm in the room that was to act as the fire room. The coordinator remained in the room until located by one of the participating staff members, as their presence indicated that it was the fire room.

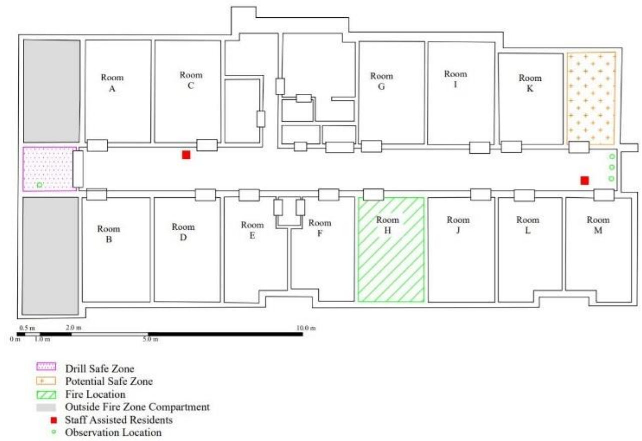


Figure E.5: Drill 3 Floorplan

When the alarm sounded, one staff member was already in the wing. "Code Red" along with the fire wing location was announced over the intercom at 0:20. A second staff member entered the wing 10 seconds later. Seven more staff entered near 1:00. At 1:10, a staff member began moving a resident toward the main safe zone (1:31) and a resident at the far end of the hall was moved back into their room to allow staff to conduct the complete egress procedure for all rooms. At 1:27, the fire room was identified by one of the staff members. At 2:00, the staff started clearing the hallway in the fire wing, and soon after the door to the fire room was closed. During the drill, two non-participating residents in the safe zone tried to enter the fire wing and were stopped by staff members outside the wing. Two staff members re-entered the fire room at 2:30, leaving soon after and closing the door as another staff member asked if they checked to see if anyone was in the room. Soon after, a custodial staff member (not part of the drill), moved a cleaning cart from the hallway and into the safety zone, leaving it directly on the other side of the fire doors. The hallway was clear at 3:00, and 15 seconds later, a staff member opened the fire room door again. At 4:00, the Evacucheck was flipped on the fire room door, after which staff members began flipping Evacuchecks on other resident room doors. The drill ended with “all clear” announced at

4:52, 20 seconds after the drill coordinator ended the drill. The drill was followed by a staff debriefing. A participating staff member discussed her confusion on how to use the Evacuchecks.

E.4.2.4 Drill 4 (Long Term Care Home – Evening time working shift)

It was the home's policy that mechanical lifts be used for bedridden residents as the home had a no-lift policy for the employees. During the fourth drill, the staff were expected to simulate using the lifts (taking one to the resident room but leaving it outside the door). The drill coordinator mentioned that the home had adopted a new procedure approximately one and a half years ago, and that the staff were still adapting to it. Specifically, the staff were now expected to check and evacuate all rooms in the wing as opposed to just the critical triangle. The drill coordinator also mentioned that fire drills were being used as both a training and evaluation tool. The floorplan of the wing where the drill took place can be seen in Figure E.6.

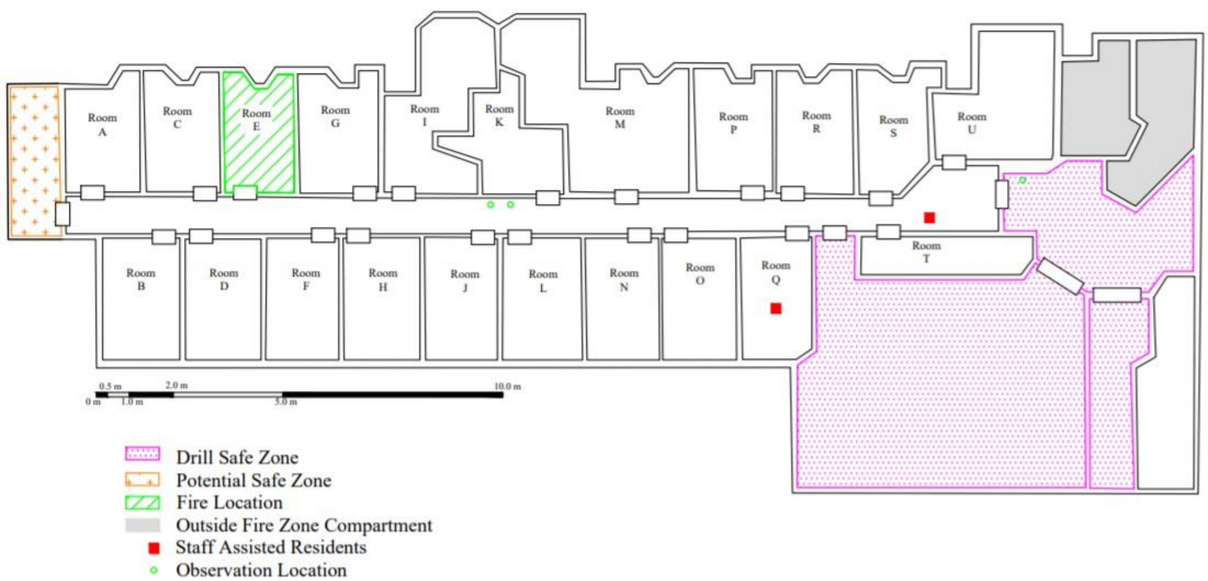
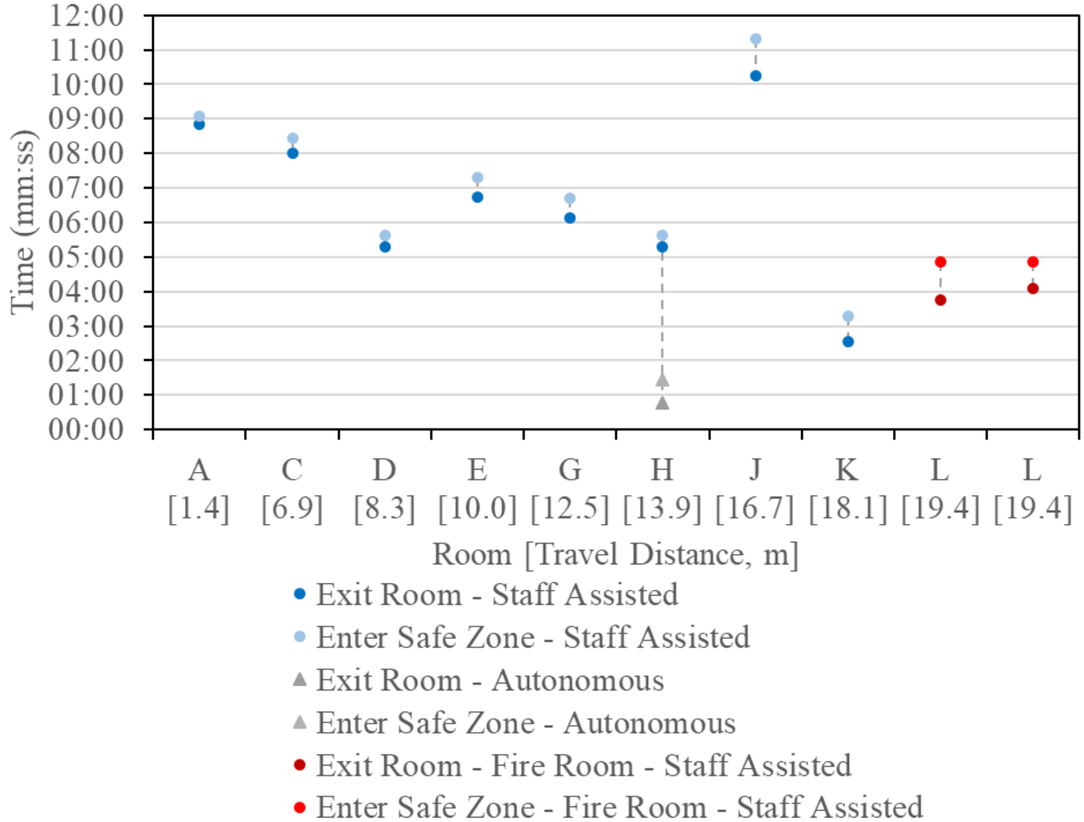


Figure E.6: Drill 4 Floorplan

The fire alarm signaled the start of the drill and 15 seconds later a resident in a wheelchair was moved from the hallway to the safe zone. A second resident was also evacuated from the hallway to the safe zone at 1:00 after two staff members spent 15 seconds debating where to take the resident. The door next to the fire room was closed at 1:41, followed by the door to the room across from the fire room. At 1:50, a third staff member entered the wing, and 12 seconds later a towel was placed at the base of the fire room door. During the following minute, four additional staff members entered the wing, standing around and waiting for something to do. At 3:12, a staff member left the wing to say that everything was done. At 3:23 "Code Red All Clear" was announced. During the drill it was noted that key elements of the home's fire emergency procedures were not executed. Examples included not simulating lift use and neglecting to close the doors and evacuate all resident rooms. In the post drill debriefing, the staff expressed that the drill generally went well, and the drill coordinator briefly discussed the tasks that were missed (using the lifts and evacuating all resident rooms).

E.4.2.5 Drill 5 (Retirement Home – Night time working shift)

In addition to the three staff, ten residents participated in the fifth drill along with three additional staff members standing in place of residents. The floorplan of the wing where the drill took place can be seen in Figure E.7. All participating residents were evacuated to the section of the hallway separated by the fire doors; the stairwell at the other end of the hall was not used.



(a)

(b)

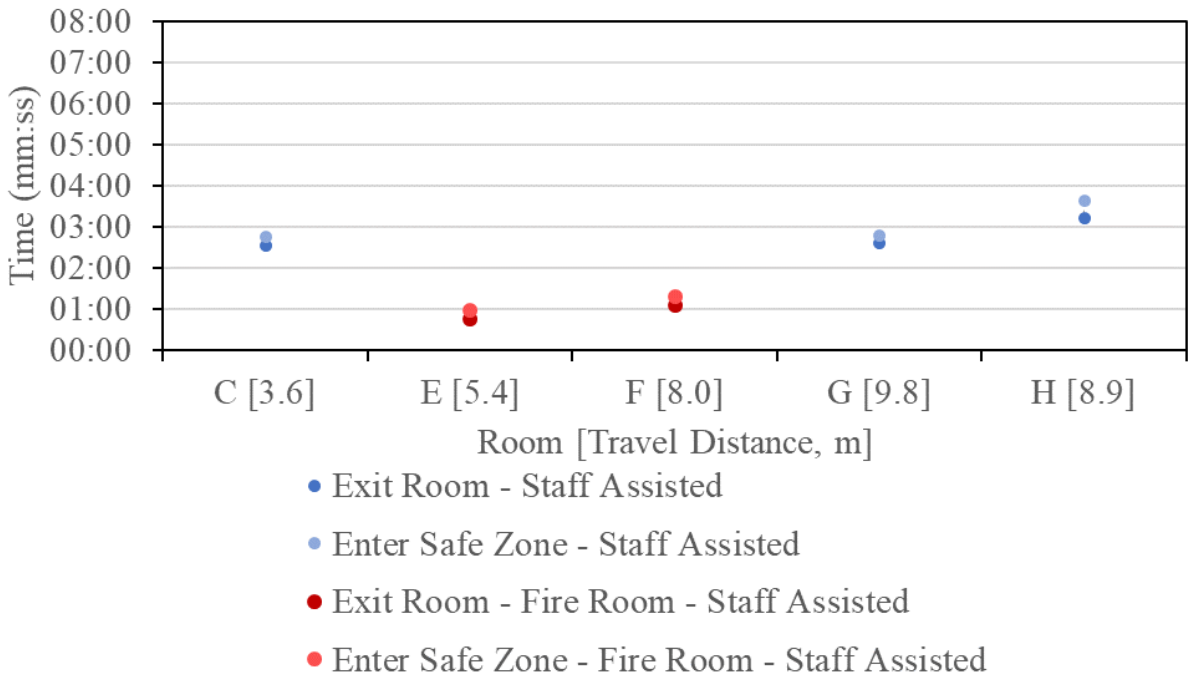
Figure E.7: (a) Drill 5 Evacuation Timeline (b) Floorplan

There were initial difficulties with the staff's hand-held notification system, so the fire room was not entered until 2:02. During that time, a resident left their room independently and made their way towards the safe zone before being prompted by one of the observing staff members to go back to their room (the reasons for this are unknown). Two staff members initially entered the fire room, but one left 30 seconds later to begin evacuating the room beside it. At 3:45, the first resident in the fire room was assisted into the hallway but tried to get back into the room. The second resident in the fire room entered the hallway at 4:06 and both residents then travelled with a staff member to the safe zone. Two staff members continued to evacuate the rooms, starting with those in closer proximity to the fire room. The third staff member entered the wing at 5:44 (they had been on the main floor meeting the fire marshal as would happen during a real fire). Once all of the rooms had been checked and the residents and staff standins had been evacuated, the rooms were then rechecked and tagged to show that the rooms were clear. During this second check, a resident was found hiding in their room, 10 minutes after the drill started. It is not clear why the resident was hiding. This resident was then evacuated, and the remaining rooms were double checked and tagged. The drill lasted a total of 13 minutes and 33 seconds.

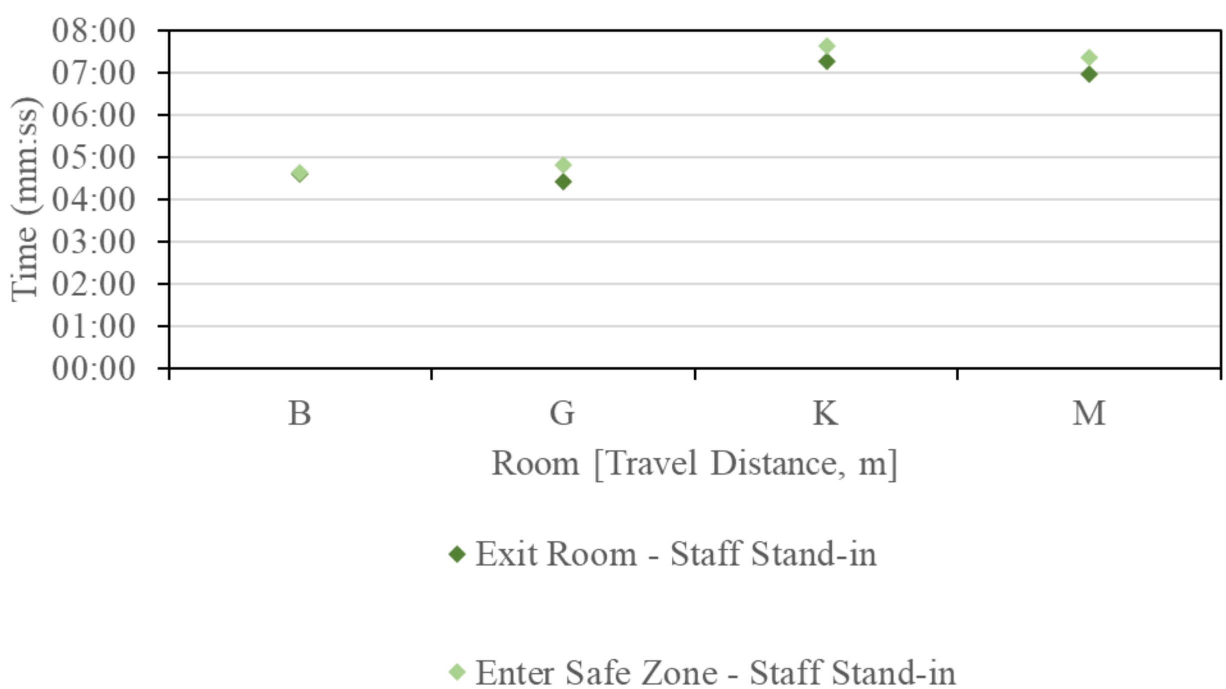
E.4.2.6 Drill 6 (Long Term Care Home – Night time working shift)

The sixth drill was observed in the same long term care home as the first and third drill, and was an annually required worst-case scenario drill. Each of the three observers were responsible for watching one staff member. As with the previous worst-case scenario drill, all the staff were aware that a drill would be taking place. During the pre-drill discussion with the drill coordinator and participating staff, the details of the evacuation were explained, roles were assigned, and staff questions were answered. Eight staff were assigned to evacuate the wing and 11 staff were designated to act as resident stand-ins. The residents chosen to be replaced by staff members were pre-determined based on their requiring a personal lift to get out of bed or their history of uncooperative behaviour. During the pre-drill discussion, the participating staff members were given the opportunity to practice the blanket evacuation method that was to be used to evacuate the staff stand-ins replacing bedridden residents. During this time, the research team selected three of the participating staff to focus on during the drill.

The floorplan of the drill location can be seen in Figure E.8. The fire alarm was set off by the drill coordinator from within the designated fire room. The first staff members to respond started checking the rooms to locate the fire. Once the fire room was identified at 0:34, the evacuation started with that room and the one connected to it via a shared washroom, and then proceeded to the critical triangle. One staff member was the designated site manager and this person was in charge of directing all of the other staff. This person did not help with the physical checking of the rooms or the evacuation of residents, with the exception of assisting ambulatory residents who only needed guidance. After the evacuation of the critical triangle, the other rooms were also evacuated. From the start of the alarm to the drill being deemed complete by the organizer and the observing fire marshal, the drill lasted 9:08. In addition to the 11 staff members, 14 residents were evacuated from the wing. During the post-drill debriefing, one of the key points discussed was how physically strenuous the blanket method evacuation was, especially after it had been done several times. The staff expressed concern over the feasibility of the night staff being able to evacuate certain residents in this manner.


08:00
07:00
06:00
05:00
04:00
03:00
02:00
01:00
00:00
Time (mm:ss)
C [3.6]
E [5.4]
F [8.0]
G [9.8]
H [8.9]
Room [Travel Distance, m]
Exit Room - Staff Assisted
Enter Safe Zone - Staff Assisted
Exit Room - Fire Room - Staff Assisted
Enter Safe Zone - Fire Room - Staff Assisted

(a)


08:00
07:00
06:00
05:00
04:00
03:00
02:00
01:00
00:00
Time (mm:ss)
B
G
K
M
Room [Travel Distance, m]
Exit Room - Staff Stand-in
Enter Safe Zone - Staff Stand-in

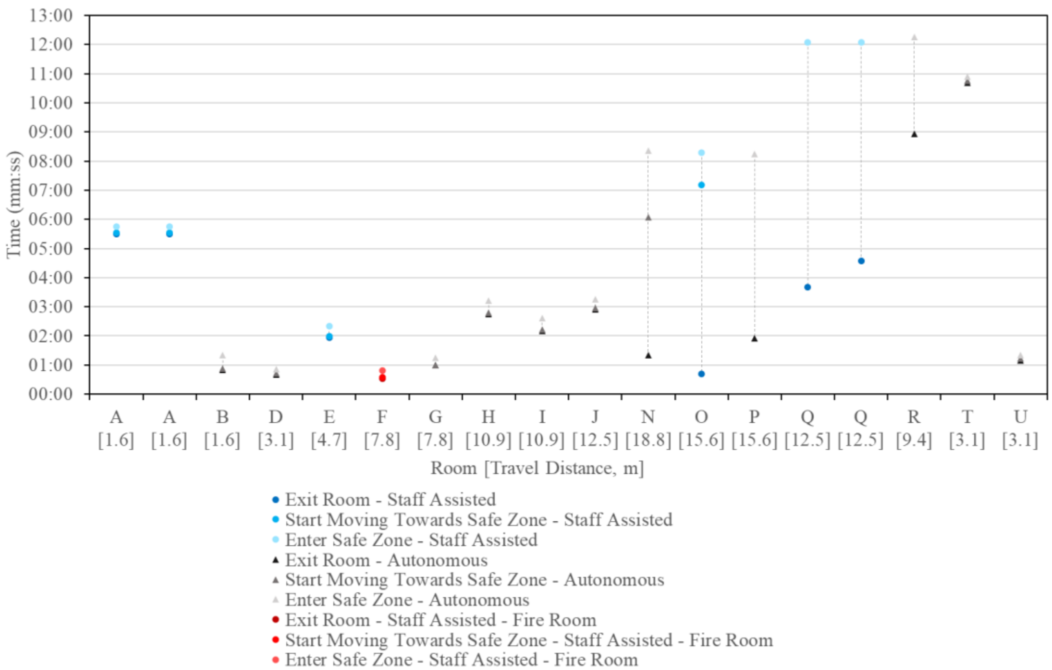
(b)

(c)

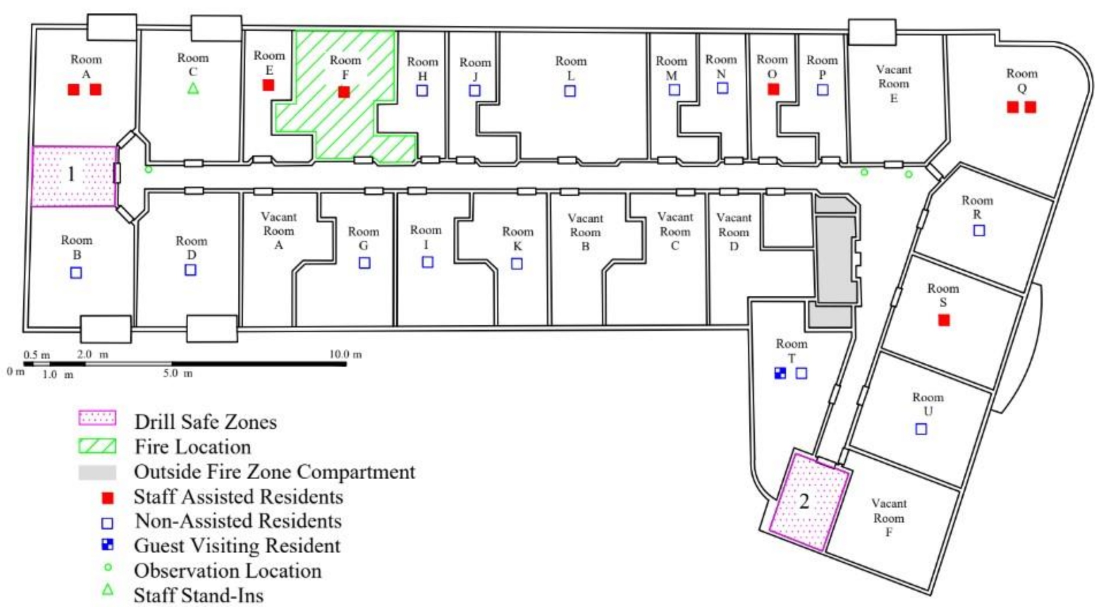
Figure E.8: Drill 6 (a) Evacuation Timeline – Residents (b) Evacuation Timeline – Staff Stand-ins (c) Floor plan.

E.4.2.7 Drill 7 (Retirement Home – Night time working shift)

In contrast to the fifth drill which was observed on a memory care floor at the same home, this drill took place on an independent care floor without fire separation doors. This meant that all residents on the floor were meant to be evacuated to the stair-wells. A total of twenty-two residents participated in the drill along with one staff stand-in, two staff members who aided in the evacuation of residents and one staff member who had to remain on the memory care floor (as per the home's policy). All three staff participated in the pre and post-drill briefings and were considered to have taken part in the fire drill. Four additional staff members who would not typically participate in a worst-case scenario drill were located in the safe zones for resident safety and supervision. The longer hallway was divided into two sections shown on the floorplan in Figure E.9. Residents on one half of the wing were evacuated to Stairwell 1 and residents from the other side were evacuated to Stairwell 2. The residents and staff were informed in advance of the date and time the fire drill would occur.



(a)



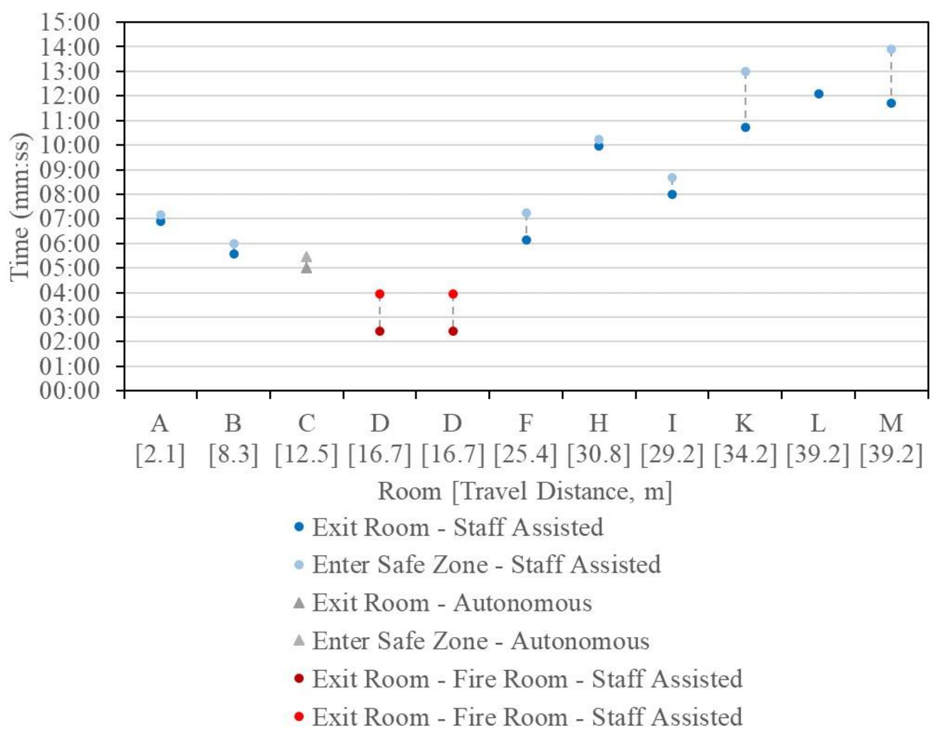
(b)

Figure E.9: Drill 7 (a) Evacuation Time line (b) Floor plan.

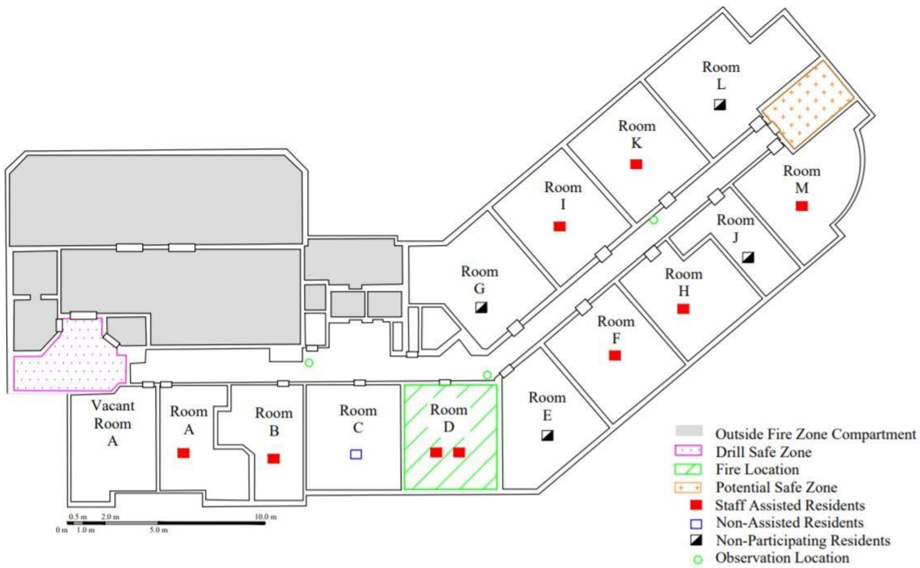
The alarm was sounded for 5 minutes at the start of the drill, then was silenced as to not disturb the rest of the building and occupants. The fire alarm was first sent to the responding nurses' communication phones, which they responded to before the audible alarm was heard by the fire marshal or observers. The evacuation followed the critical triangle method. The resident in the fire room required staff assistance and was observed to have exited the room at 0:32, pushed in a wheelchair by the staff member, and then entered the safe zone at 0:49. Two ambulatory residents evacuated on their own once the audible alarm began. Most other residents evacuated when instructed by the staff member, but some were confused about the procedure. Those residents exited their room and sat on their walkers, awaiting staff assistance to the safe zone. One room housed a married couple in which the spouse would not leave without the other resident who insisted they finish showering before evacuating. The second staff member, who had attended the fire command center, entered the fire drill wing at 4:05. Occupied and vacant rooms underwent two checks before an "All Clear" marker was placed on the door handle, indicating the room was empty. There was one wheelchair-bound resident who independently initiated evacuation once the alarm sounded but was not observed to have entered the safe zone and was later seen re-entering the floor via elevators. The drill ended at 14:28. A key finding was that although this drill occurred on an independent care floor, a majority of residents still required verbal cues from staff to initiate evacuation and some even thought it was the staff's responsibility to guide each resident to the safe zone. This highlighted the important leadership role of staff in these establishments even if the residents were perceived as independent.

E.4.2.8 Drill 8 (Retirement Home – Night time working shift)

The eighth observed drill was held on an assisted living floor that was not secured; it had two wings separated by a fire door to create compartmentation shown in Figure E.10. As this was an annual worst-case scenario drill, the staff of the building were notified of the fire drill details in advance while the residents were notified of the date but not the time that the drill would occur. The researchers had been told that 17 residents would be participating in the drill, however, on the day of the drill they were informed that only 14 would be participating. Of these 14 residents, four did not end up evacuating during the drill (two refused to evacuate and two were told by staff that they did not have to evacuate) and therefore data was collected for 10 residents. Three on-duty night staff were in charge of evacuating the residents. Additionally, four observing administrative staff, two maintenance staff and two fire marshals were also in attendance on the fire floor along with the three research observers and the two drill coordinators. The floor was separated into two fire safety zones by a fire door to which the residents were evacuated past into the safe zone following the critical triangle method.



(a)



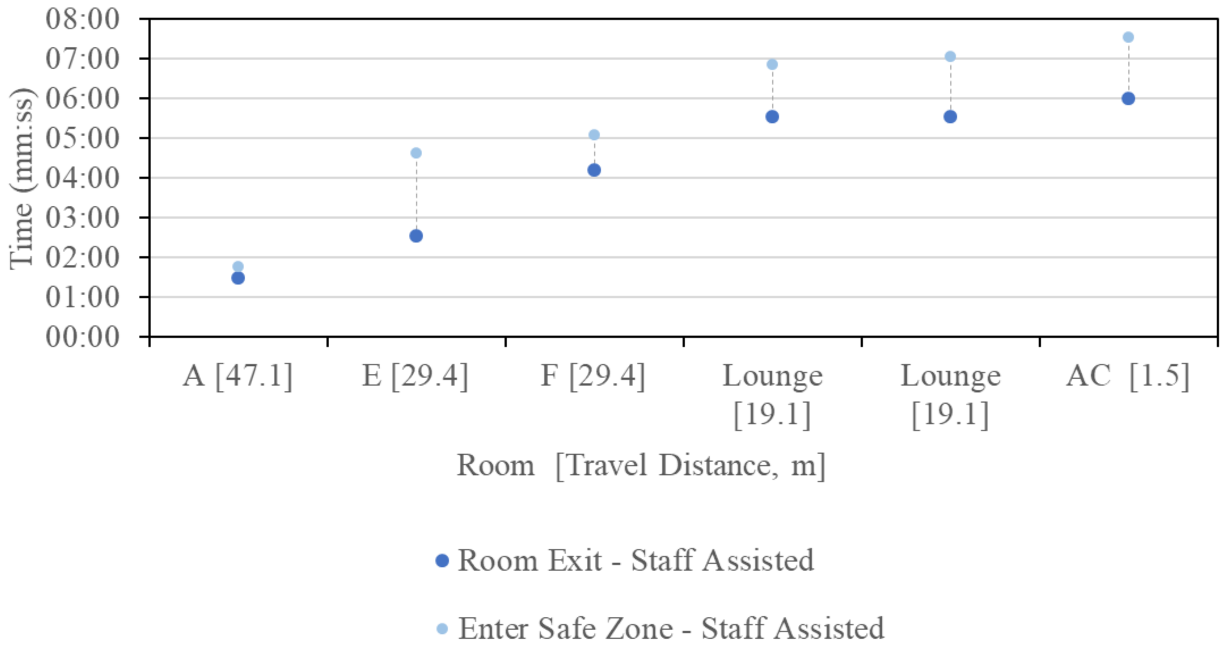
(b)

Figure E.10: Drill 8 (a) evacuation Timeline (b) Floorplan

On arrival, staff members were overheard discussing the proper procedures for the drill. This was a silent drill therefore the fire marshal indicated the start of the drill. One staff member was required to go to the fire control center to discover where the fire was located while the other two entered the fire wing and awaited the fire location. Once the location was known, the first staff member evacuated the fire room while the second staff member began notifying the resident in the adjacent room of the evacuation. The residents occupying the fire room were confused and exited the room at 2:25 and then entered the safe zone at 3:57. A resident who did not require assistance other than a verbal cue then evacuated to the safe zone. The third staff member re-entered the wing almost 8 minutes after the drill started. For both occupied and vacant rooms, one check was conducted before the room was declared empty of residents and a marker was hung on the door. One staff member was repeatedly reminded to properly close the door after exiting the room with a resident or after the check. The second staff member encountered two non-participating residents and instructed a third resident that participation was not necessary. This staff member then proceeded to jog with said resident's walker to the safe zone in an attempt to emulate the evacuation actions. At 11:30, visitors entered the fire drill zone via elevators and stood in the lobby area. The fire marshal did not require staff to evacuate a wheelchair-dependent resident to the safe zone if it caused undue stress to the resident. The last resident who entered the safe zone did so at 13:55 and the drill was deemed complete soon after. In the post-drill discussion, the fire marshals emphasized that the building was sprinklered and had compartmentation therefore firefighting actions by staff were not required.

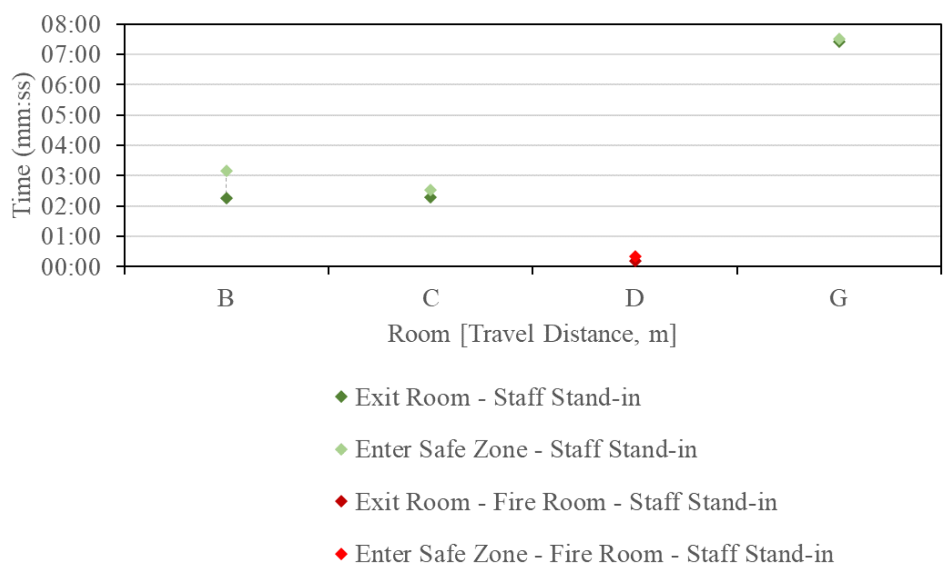
E.4.2.9 Drill 9 (Retirement Home – Night time working shift)

Having just recently opened, this home had been receiving occupants two months before the fire drill was observed and had approximately 50% occupant capacity at the time of observation. This was the first annual fire marshal-attended drill the retirement home underwent with resident participation. This included three on-duty staff, four staff stand-ins and six residents on a secure memory care floor which required a pass code to exit into the stairwells, one of which was used as the safe zone. The floor had 33 rooms; only ten were occupied, as shown in Figure E.11. Some residents were notified in advance of the drill and were moved to alternate floors. Staff stand-ins were put in their place with the respective mobility assistance devices.



08:00
07:00
06:00
05:00
04:00
03:00
02:00
01:00
00:00
Time (mm:ss)
A [47.1]
E [29.4]
F [29.4]
Lounge [19.1]
Lounge [19.1]
AC [1.5]
Room [Travel Distance, m]
Room Exit - Staff Assisted
Enter Safe Zone - Staff Assisted

(a)



08:00
07:00
06:00
05:00
04:00
03:00
02:00
01:00
00:00
Time (mm:ss)
B
C
D
G
Room [Travel Distance, m]
Exit Room - Staff Stand-in
Enter Safe Zone - Staff Stand-in
Exit Room - Fire Room - Staff Stand-in
Enter Safe Zone - Fire Room - Staff Stand-in

(b)

(c)

Figure E.11: Drill 9 (a) Evacuation Timeline – Residents (b) Evacuation Timeline – Staff Stand-ins (c) Floorplan

This was a silent drill where no audible alarms were used, but the staff went through the motions of going to the fire command center (located at the Nurse's Office on the same floor) and using the mobile communication phones to relay the location of the fire. The fire room had a staff stand-in using a walker and was evacuated by staff at 0:21, entering the safe zone at 1:43. The second staff member began evacuating residents 59 seconds after the drill began. The third staff member realized they were supposed start the drill on a different level and went into the elevator lobby, then "re-entered" the fire wing at 1:19. The staff followed the critical triangle evacuation procedure similar to previous drills. A couple of residents were in the communal lounge area at the time of the drill and exited the lounge at 5:32, entering the safe zone at 6:52 and 7:03. All residents required staff guidance from their initial locations to the safe zone. All the rooms were checked twice before an Evacucheck marker was flipped up, indicating that the room was cleared. The last resident was evacuated from their room and exited the wing at 7:32. The drill ended soon after, at 7:38. Observers noted issues with the room doors not fully closing and the lack of fire separation doors on all floors of the building. In the post-drill discussion, the fire marshal suggested that the residents in the fire wing should be evacuated but residents from the rest of the building could stay in place due to the building's compartmentation design. This highlighted the reliance on compartmentation from the building design for the fire safety plan.

E.5 Discussion

E.5.1 Observed Trends in Behaviour and Actions

Through the observation of the nine fire drills discussed above, several similarities and differences in resident and staff actions and behaviours were identified. A high level of staff dependence was observed. Table E.5 provides the types of staff actions and behaviours observed as well as their frequency and probability of occurrence based on those observed and subject to limitation (see Section 5.3). For consistency, only the actions of the staff members who were the primary focus of the observers are included. Drill 1 was excluded as the recorded actions were not associated with specific staff members and therefore could not be tallied. Table E.5 shows there are several actions that were observed in multiple drills and by numerous staff members. Examples include entering the fire wing, locating/entering the fire room, checking rooms for residents and guiding residents to the safe zone. The observed actions were influenced by the type of drill being observed and in part due to the requirements of relevant legislation. For example, the number of staff members who evacuated residents was quite low in the first four drills (all monthly drills), especially compared to the percentage of overall staff participating in the drill. This is likely a reflection of the fact that during these drills the staff are not required to evacuate residents. While they are supposed to evacuate residents who are willing and able to participate, it was seen that this was not often done, be it for reasons of not disturbing the residents or because the staff were unaware that they were supposed to. As the staff during the worst-case scenario drills knew the location of the fire room prior to the drill, they were not observed spending time looking for the fire while the staff in the monthly drills generally did. It is also important to note that while Table E.5 groups the observed actions into categories and appears to follow a linear progression from drill start to drill end, there is evidence of observed actions occurring multiple times at various times during the drills. For example, staff seeking information from each other occurred at various times throughout the drills.

Less data was collected for residents as they did not egress independently for most instances and focus was instead on staff interactions. Some observations included residents seeking information by coming to stand at their doors prior to being evacuated, residents waiting for other residents before evacuating (e.g., couple), finishing tasks (e.g., showering), bringing belongings with them (e.g., tea), and hiding. The action of hiding requires more careful study to allow design to account for this in the future. It was also observed that many residents, even those in retirement homes where nursing care is not provided, required assistance to evacuate (40 of the 56 residents who were recorded). In some cases, this meant that the staff had to guide and walk with them to the safe zone. In other cases, this meant verbally prompting residents who were waiting at their bedroom doors. In both cases, the staff had a large impact on the evacuation of residents as the worst total egress times seemed to be most affected by low staff and high proportions of residents as per Table E.4. For each drill the number of residents is low, and in some cases staff stand-ins were present limiting the quantifiable value of the drills. Further limitations of this data are articulated within Section 5.3 of this paper.

E.5.2 Evacuation Timeline and Order

Figures E.7 – E.11 show the observed room exit and safe zone entrance times, as well as the distance travelled (only to a point of safety, not the entire building) for participants in Drills 5 through 9. Given the high dependency on staff, the pre-evacuation times were largely determined by when a staff member assisted or prompted a resident to evacuate. Staff acting as Stand-ins for residents are presented in separate figures (E.7- E.11) where data is available (figures E.8 and E.11), as they were not credible movement profiles that represent residents, but are still important to include for the purposes of recounting the actions and workload of the assisting staff and to illustrate that they have limited credibility in their use for training in real drills illustrating faster movement speeds than the aging population data. These figures show a general trend of evacuating residents based on their proximity to the fire room, which was in line with the critical triangle method and evacuation strategy mentioned earlier. The variation in time spent between exiting a room and entering the safe zone is also clearly visible in the graphed data. It is important to note, however, that this does not always correspond to the movement time and speed of an evacuee. As was observed during Drill 7 and can be seen depicted in Figure E.9, a number of residents exited their rooms independently or with prompting and then remained in the hallway outside of their rooms until they were prompted again or guided to the safe zone by a staff member. It is therefore important to make sure that when using data from a fire drill it is clear whether or not this is represented in the data. True autonomous behaviour is a very gray concept when considering elderly populations. Figures E.7 – E.11 show residents who required a staff member to walk with them to the safe zone (this was defined as staff-assisted for this study) and residents who reacted and evacuated entirely on their own or required only verbal prompting (defined as autonomous herein). The residents were classified this way to be able to see potential differences in the time spent walking from a resident room to the safe zone. This classification is useful for recording movement times (and therefore "agent" speeds when geometry is considered); however, it does not articulate the number of residents who relied upon any form of interaction with staff – which will also be important in modelling. In that case, the number of staff-assisted residents would be higher.

Figure E.12 illustrates pre-movement times of residents and residents with staff only. It does not include staff stand-in values. Table E.6 and Figure E.12 are provided with specific limitation, in that: they implicitly include the movement of staff with residents; building geometry is not included; and that they are only based on collected resident data which is of low sample number. In all but two drills, staff were always present when the drill began. The latest time for the first staff member to enter the fire wing was 0:24. This tabulated information, based on drills with resident engagement may be useful in table form for practitioners developing preliminary models or algorithms but additional data should be collected (see Section 5.4) prior to use. The measured average speeds (only for residents or residents being assisted – we have not computed speed values for staff stand ins as the data would not be appropriate to be mixed – inclusion would result in a higher movement speed) recorded in the drills (which reflect changes in speeds due to acceleration/deceleration based on measured linear distance from the floor plans and time door to door as taken at the drills) were derived as follows based 56 data sets of resident and assisted resident distance and time data: Average 0.33 m/s, minimum 0.02 m/s, maximum 1.81 m/s, mean 0.3 m/s. This movement profile is subjected to additional limitations which are described in detail within Section 5.3. The authors caution that these data sets do not include anthropometric aspects of movements which should also be studied in a more holistic data collection and modelling study, but these current values do provide practitioners a valuable data set that can be utilised in conjunction with preliminary modelling of care and retirement homes. Subsequently we have limited the scope of this profile generation as it is in need of additional building particularly as it implicitly includes the assistance and non-assisted residents in its calculation. The manuscript does provide the requisite information for practitioners to build preliminary models with exact data given for each resident as well as exact measured floor plans with travel distances noted that can be incorporated into a preliminary model. The quantifiable data is conservative in that the speeds are generally slower than those reported in existing literature for non-autonomous movements such as the SFPE handbook. While limited in value, this data yields a starting point for comparison in future studies and for specific modelling development of case specific movement scenarios or algorithm development (assisted movement for example). Preliminary models may also be commenced focusing on programming behavioural actions as observed. The authors plan future work to study the generation of appropriate models. Figure E.12 provides the reader with a visualization of the evacuation timeline of Drill 5 through 9, though inherently does not include the effect of differences in architecture between each drill in different buildings which would be used for travel velocities it is also based on low participation in the drill and limited by low recorded data where some residents were not recorded.

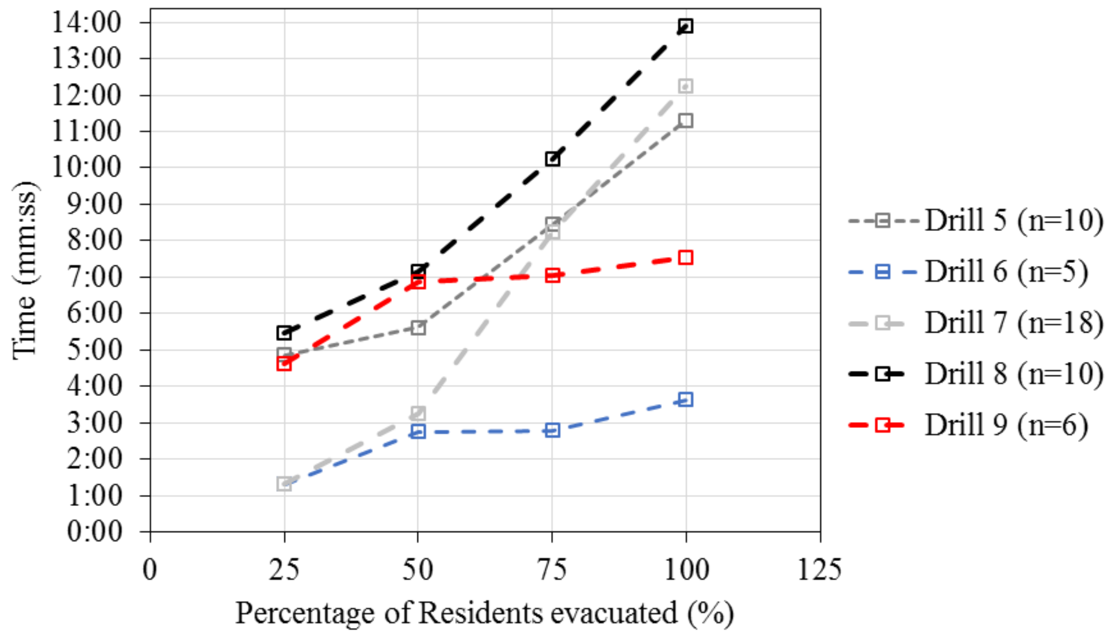


Figure E.12: Evacuation Profile assuming implicit staff and resident behaviour (see Table E.6 and Section E.5.3 for limitations)

E.5.3 Limitations for Using Fire Drill and Movement Data

It is evident in looking at these drills that there are numerous modifications that are made (intentionally or unintentionally) during a drill that would not be possible given an actual fire event. In some drills, more staff were noted to have played a role in the drill than were supposed to. These staff were observed closing doors to resident rooms, tagging doors and supervising residents in the safe zone. In reality, during the night shift which these drills were supposed to be simulating, these additional staff would not be present to assist. While it is understandable why these staff would be present during a drill for additional resident safety, it is not representative of a real fire. During such an event, the on-duty staff would be responsible for evacuating the residents as well as monitoring them within the safe zone. Additionally, the impact to pre-evacuation and preparation times, as well as the potential increase in resident resistance to evacuation as a result of being woken up and potentially wanting to get dressed or gather belongings, is not represented in these worst-case scenario drills.

Another trend that was seen during all but one of the observed fire drills was that of residents evacuating (either assisted or autonomous) to only one safe zone, regardless of their proximity to the second (typically the stairwell). While it makes sense why this would be done for ease and convenience during a simulation, given the mobility and mental state of many residents (e.g., having residents wait in a hallway is easier and more practical than a stairwell), it is not representative of all of the safe zones that residents would be evacuated to in an actual fire. Often not all residents were evacuated, even during worst-case scenario drills. In the observed monthly drills (Drills 1-4), it was seen that very few residents were evacuated at all. In the later drills where more residents did participate, staff stand-ins generally took the place of residents who would have greater difficulty evacuating (uncooperative, reduced mobility, etc.). As was seen in Drill 8, a staff member jogged from a resident room to the safe zone with a walker, “simulating” the evacuation of that resident. Given the mobility impairment of this resident, this was not an accurate representation of the resident’s evacuation. These resident exemptions or replacements not only affect the time required to complete the drill (preevacuation time, walking speed) but also have a large impact on the realism of the drill. It is understandable why LTC and retirement homes do this, to better ensure the immediate safety of their residents and staff as well as reduce the level of disruption caused to both. However, this does have an impact on the credibility of potential data and the use of these drills for training and evaluation of staff in such homes.

The roles played by the drill coordinators and fire marshals present during the drills were also seen to impact the drills. During the worst-case scenario drills, the observing fire marshals and/or drill coordinators were observed to interact with or prompt the participating staff members.

This ranged from telling staff that they should be tagging the evacuated rooms to telling staff that they did not have to evacuate residents to the safe zone, as was seen in Drill 8. In this specific case, the fire marshal said that the only important time that the staff were being evaluated on was the time required to prepare the residents and bring them into the wing hallway (not take them to the safe zone). This information not only impacted the subsequent actions of the staff who then did not finish evacuating a resident (therefore impacting the accuracy of the drill's representation of a "real" fire event), it also contradicted what had been observed during the other worst-case scenario drills. In most of the post-drill discussions with the staff, the fire marshals and/or the drill coordinators commented on the impact of fire compartmentalization and sprinklers, stating that in the case of a fire, the staff would have plenty of time based upon the fire rating of the structure (door rating for example) to evacuate residents. In relation to this, no comment about the impact of smoke on tenability in relation to the safe egress time, nor difference in real to standard fire was discussed. The impact of staff and resident actions, such as doors being left open or the fire room being entered multiple times, are not made clearly apparent.

Looking specifically at the considerations warranted by the differences between the earlier and later drills observed in this study, it can be seen that each have advantages and disadvantages. The first four drills in this study were largely influenced by their type (monthly drills not requiring resident participation) and the residence type (long term care homes where residents were highly dependent on staff). In the case of these four drills in this study, the observation style also had an impact (focused on general observations, less on evacuation timestamps). These four observed drills did not provide the type of data that could easily be incorporated into an egress model (pre-evacuation times, walking speeds, etc.). However, they did serve to provide an understanding of general fire evacuation procedures in these homes. Additionally, as the staff and residents were not informed of the drill prior to it occurring, the initial response to the alarm reflects more closely their response to an actual fire. This realism can fade once the drill coordinator and observers were observed and no fire or smoke is found.

Drills 5 through 9 in this study have their own set of opportunities and challenges that need to be understood when looking to use the collected data. Primarily they showed low overall participation by the residents. While there were some autonomous resident evacuations observed, staff verbally prompting residents to evacuate or physically preparing them for evacuation and walking with them to the safe zone was a very prominent occurrence. This showed that even in retirement homes where residents do not require the same level of daily care as in LTC homes, staff still play an important role in fire evacuations. This information is valuable for models as it shows the importance of modelling the impact of staff and it provides examples of times associated with different staff actions. With respect to the general limitations of annual, fire marshal-observed, worst-case scenario drills, there are a couple key considerations. The staff who will be participating in the drill are aware of the drill before it happens. As these drills are being used for official evaluation by the fire department/province, the homes are also allowed to "practice" the drill before it is observed. While this is beneficial in that it ensures that staff (and potentially residents) are better prepared should a real fire occur, it reduces the realism of the drill (showing the conflict of using drills as training and evaluation tools). Staff stand-ins also affect the realism of the drill, given that they will not react or move in the same way as actual residents – for this reason we do not consider this data within the calculation of any movement profile in this paper.

E.5.4 Future Work

Research into fire evacuations in LTC and retirement homes, and the inclusion of human behaviour in fire into egress models in general, needs to continue so as to further develop models that are more representative of actual evacuations. The use of the Protective Action Decision Model (PADM) developed by Lindell and Perry holds great potential for being used to create a conceptual model of human behaviour based on data such as that collected in this study.[24,25] The PADM shows the process of decision making during emergencies, describing the steps and factors that influence the adoption of protective actions (in the case of a building fire, evacuating or seeking refuge for example).[25,26] Such a conceptual model could then be used to support the creation of computational models for use within egress software, therefore creating more accurate and realistic models of evacuations of the built environment.

Validated and verifiable models can be explored with the pre-movement and movement data herein with limitation as noted in Section 5.3. Figure floorplans can be scaled appropriately and built with incorporation of the incorporating the movement (pre-movement and movement) profiles derived from the data collected. As sample numbers are low, the authors suggest that prior to detailed modelling studies that additional data be collected where anthropometric data is also collected.

These models must also begin to incorporate the impact of toxicity and smoke as it has been shown to have a large impact on evacuees.[27] The presence of smoke can not only affect visibility, but also response time and movement speed.[28] Our understanding of toxicity and smoke plays a role in building compartmentalization, which, as seen in this study, is very much relied upon in residences such as LTC and retirement homes. Some studies have also shown that certain health conditions, such as cardiovascular disease, can impact one's susceptibility to smoke.[29] This may therefore have a great impact on residents of LTC and retirement homes and should be studied further.

E.6 Conclusion

This study of nine drills in Canadian LTC and retirement homes has shown that valuable data can be collected from the observation of fire drills. Information about residents, the interactions between staff and residents, the type of actions that are undertaken by staff during the evacuation process and the general procedures that are followed was collected. This information provides a better understanding of evacuations in such care homes and acts as a source of data that can be used to help inform egress modelling software. These drills demonstrated that emergency egress in long term care and retirement homes is highly staff dependent with over 72% of residents requiring full assistance in evacuation.

This study has also shown that there are a number of important considerations that must be made when choosing to conduct this type of data collection or when using data collected by such means. The use of in-person observation and written note-taking can be used in cases where cameras are not welcomed or allowed. When specific observation objectives are defined, and the observers can focus on specific staff and/or resident participants, valuable data can be collected from places that would otherwise not have allowed researchers access. However, if the scope of information sought is too broad or the situation overwhelms the observation and recording capacities of the observers, the completeness of the data collected can be reduced.

The critical point of this methodology is its ethics implications; residents in care homes like these may have conditions such as dementia, which can make it difficult for them to consent to being included in the datasets via other methodologies such as video recording. The methodology herein tailors to how similar and future studies may be conducted within restricted research environments , however; also notes the various caveats which can influence the usefulness of the data that would be collected.

It is easy to see that data from actual fire events would provide the most accurate data, and that collecting data from such events is important in further developing our understanding of human behaviour during such events. However, this data can be very difficult to come by. Over the course of this study, the researchers made continual efforts to reach out to the owners of local LTC and retirement homes that had experienced real fires in recent years for camera based and real event data. To date, all of these invitations have gone unanswered. Given the difficulty of being able to access such data, fire drills pose a more readily available source of evacuee behaviour information of vulnerable populations. Through drill observation, important information about the behaviours and actions exhibited by staff and residents in care homes and the procedures that are supposed to be followed during fires can be obtained.

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Appendix F: Authenticating Crowd Models For Stadium Design

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Abstract

Crowd simulation software is an emerging technology used to validate and verify stadium design in terms of total egress and safe densities of large crowds. To model occupant movement, this technology can sometimes rely on dated and non-representative parameters. Where this limitation may be overcome with an array of movement input variables assigned by the user, currently these inputs lack diversity in profile representation. Limited studies have worked towards developing walking speeds for different demographics or are project-specific to stadium design. Even more limited are studies of complex profiles such as physical impairments and obesity. Circulation and evacuation models are therefore challenged in their ability to diversify crowd demographics and represent realistic demographic conditions. With realism not assured, there are a range of uncertainties that can be introduced by assumptions from the user.

To overcome these limitations, this research seeks to perform an analysis of the demographics seen at a stadium, establish a set of walking speeds, and use this to authenticate available egress simulation models. Herein, established behavioral profiles were used to represent children, young adults, adults, seniors, families, overweight adults, overweight seniors, as well as users of canes, crutches, and walking sticks, individuals carrying oversize luggage, and individuals requiring assistance. This data was then used to construct models in conventional crowd simulation

software to compare with earlier modelling methods that assume the more dated and non-representative metrics for movement.

Individualizing profiles in total egress modelling provides a step towards reducing uncertainties of human behavior and producing more reliable frameworks for crowd movement predictions. The importance of diversifying input speed parameters is revealed in comparison to previously relied upon methods that limit crowd behavior to a single range of movement, and additionally, advocates for project-specific data acquisition. Current limitations of the models are discussed, and suggestions are made for continued studies on movement behavior and improvements to current software.

F.1 Introduction and Background

Stadia design is a unique area of engineering. Not only because stadia accommodate extremely large crowds – commonly in the tens of thousands – but more so because they must accommodate for the mass ingress and egress of these crowds, within short periods of time. This poses unique scenarios and credible areas of concern for practitioners, particularly regarding safety and accessibility.

Crowd simulation software is an emerging technology used to model and assess pedestrian dynamics of large crowds in stadia. This can be configured for regular circulation, ingress, egress, full and partial evacuations, and emergency situations. It is an important tool for practitioners in the validation and verification process of designing a safe usable space for people. This software allows the ability to specify parameters to simulate the desired movement scenario and populate the space with a desired population. Profile parameters are largely dependent on the walking speed in metres per second (minimum, maximum, mean, standard deviation) and radius in metres. Demographic distribution refers to the proportion of different profiles prevalent in the crowd.

Crowd simulation software is founded on the construction of behavioural profiles for people, and the construction of a 3D environment for these people to inhabit. Behavioral profiles are commonly based on social force or similar inverse steering algorithms, and are dependent on industry standard metrics, and project specific data input. These parameters however pose limitations on the functions and the outputs of crowd simulation models. This is because industry standard metrics are not always genuine to the specific population at hand, but rather use a generic distribution to describe the agents. Fruin Distribution, for example, is a commonly used metric that assigns speeds based on the density of the crowd. This results in flows tuned to math the data in John Fruin's Pedestrian and Planning design, based on studies produced nearly 50 years ago [1] [2]. And although the user can overcome some of these limitations by specifying an array of project-specific input data, this still poses some limitations. As discussed in the SFPE foundation on Movement and Anthropometry report [3] the required inputs currently lack diversity in movement representation, are relatively unavailable to use in practice, and are otherwise out of date.

Limited studies have worked towards developing walking speeds for different demographics; however, none (to the awareness of the authors) are project-specific to stadium design nor provide usable statistics regarding more complex agent profiles, such as those with physical impairments and obesity. Models are therefore challenged in their ability to diversify crowd demographics and represent realistic evacuations. With realism not assured, there are a range of uncertainties that can be introduced by assumptions from the user.

To overcome these limitations, this research, as supported through the SFPE foundation project on Movement and Anthropometry, works to configure four comparative crowd simulation models to analyse the impact of authenticating models with project-specific data as opposed to relying on industry standard metrics. Using a stadium event that takes place annually at York University, the authors analysed the crowd to establish a set of agent profiles and demographic distributions to model the following egresses:

Model 1: Current Default Parameters

Model 2: Manual Input Parameters for Average Population (Not Inclusive of Complex Profiles)

Model 3: Manual Input Parameters for Observed Population

Model 4: Manual Input Parameters for Forecasted Population

By simulating these models, the authors reveal the importance of using increasingly project-specific data and discuss the remaining limitations. The fourth simulation is additionally used to forecast modelling scenarios that work toward fully inclusive designs. Steps for model configuration and best practices used in crowd simulation software are also provided.

F.2 Model Configuration

The stadium considered in this study, is a tennis stadium located in York University, Toronto, Canada. It was built in 2004 and has a capacity of 12,500 people. Using this stadium enabled the authors to build off previous studies conducted at the same location, and use this data to produce the authentic models described in the later sections. Walking speeds were established for a variety of demographics observed at the event, placing particular focus on persons with mobility-impairments. All data collection was recorded using video footage analyses; thus, all cases were established using visually discernable cases. Further details to this data, and the method of collection, can be referred to in the SFPE foundation on Movement and Anthropometry report [3]. As within the foundation report, the authors advise that practitioners wait until the final papers on each infrastructure are released prior to utilising the movement speeds. These still require validation. In the mean time for research purposes such as those herein they are suitable to exemplify areas of further work.

The stadium was constructed to scale in AutoCAD using blueprints provided by the stadium officials (Figure F.1), and then imported as a CAD file to MassMotion (MassMotion 2020, Version 10.5.6). All models simulate low-motivation scenarios, meaning they are not representative of emergency evacuations, for example. Pre-movement times were consistent in all simulations, based on the findings of Aucoin [4] in a Canadian stadium egress study. All models were given the same premovement parameters; a mean of 36 seconds, a standard deviation of 19 seconds, with a normal distribution. This enabled the authors to compare the models based on varying profile parameters and demographics distributions to isolate the impact of authenticating models with project-specific data to overcome limitations of industry standard metrics.

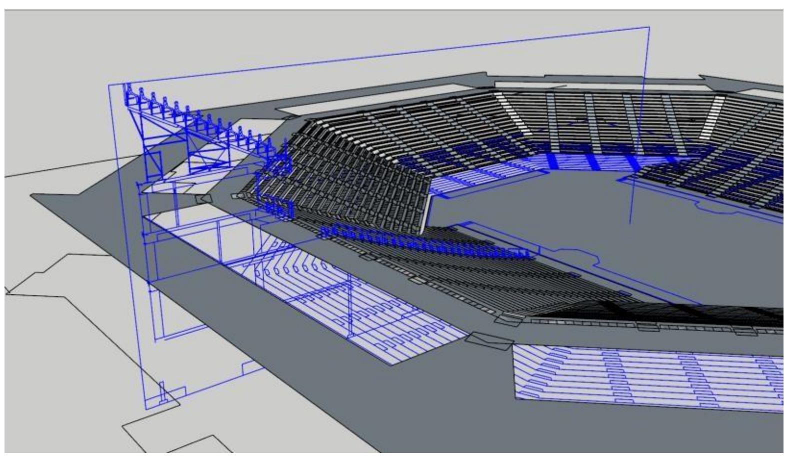

Figure F.1: York University Model Generation.

F.3 Profile Parameters

The following table (Table F.1) outlines the profile descriptions that are used in the simulations. This outlines the input speed and radius details that are required by the software. For modelling purposes, the profile radius is defined as half the distance from shoulder to shoulder, in meters [1].

The default profile speed and radius parameters are those which are pre-set and provided on default by the software. Using this software, the default settings describe the Fruin Commuter profile as the standard metric, which is commonly adopted in crowd simulation software.

The remaining walking speed parameters were derived through collected film footage by the authors. In 2018, the authors were granted access to the York University stadium for filming and interviewing attendees but were not allowed to manipulate ground conditions or invoke emergency conditions of egress. The building's site contained a pedestrian village with various restaurants, shops, and isolated events. This gave the authors a unique opportunity for the study of contemporary movement data sets of accessibility issues. Ethical considerations for filming were addressed by having each patron ticket explain that filming is taking place, disclosing this to attendees. The data collection method allowed the authors to consider vulnerable populations. Over the course of the summer, 1.7 TB of 1080p resolution video and a series of images were collected and studied to formulate movement profiles. Films were taken from carefully selected vantage points in the stadium and grounds using a series of Canon Mark III 5D cameras and GoPro 7s. Approximately eight students were required to participate in data collection. These recorded videos are still being studied by York University researchers for movement speeds and behavioral cues for final journal consideration. Figures F.2 and F.3 illustrates various locations of filming where data was derived from.

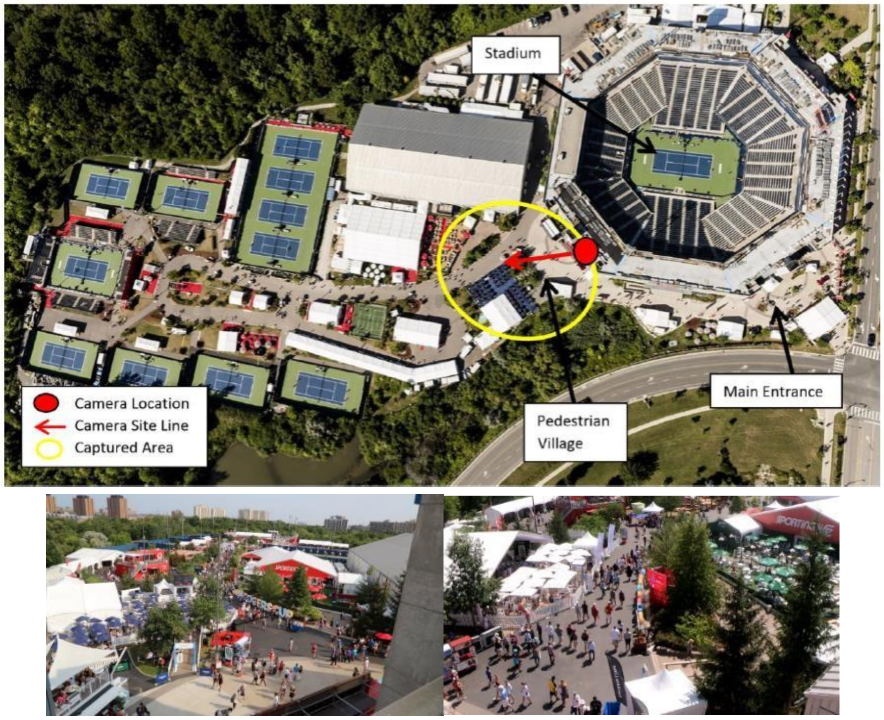

Figure F.2: Toronto Tennis Stadium and Pedestrian Village Filming.

Figure F.3: Toronto Tennis Stadium Selected Filming Angles.

The Able-bodied profiles are representative of average profiles for children (4yo-12yo), young adults (13yo-25yo), adults (26yo-64yo) and seniors (65yo+), all of whom are not subjected to any of the following mobility limiting impairments. Mobility-limiting impairment profiles include mobility cases that result from psychological or physiological abnormalities. This includes the use of a cane, crutches, walking stick and requiring assistance by another person, in addition to others which were not adopted for this study. Overweight and obese profiles are used to described adults, young adults and seniors who are overweight and/or obese. Other mobility limiting profiles are used for nonphysical impediments, such as the use of oversized luggage. Some profiles were not adopted in this study such as intoxication which requires further research.

As seen in Table F.1, the default radius is set to 0.25m, and within the manual, it is advised that any modifications to these parameters be within a range of 0.15m to 0.40m [1]. Data acquisition for radius parameters of the remaining profiles have not yet been established, nor are of accessible use to the authors. The authors therefore rationalized the respective radii using the above criteria and the existing footage (as above) to expand upon the SFPE foundation study [3] by analysing and approximating radius characteristics for the purpose of this study. The authors acknowledge that this is not an exact average, and further study is required to publish reference data.

Table F.1: Agent Profile Descriptions.

	Speed (m/s)				
Agent Profile	**Min**	**Max**	**Mean**	**SD**	**Radius (m)**
Default Profile					
Fruin Commuter	0.65	2.05	**1.35**	0.25	**0.25**
Able-Bodied Profiles for Unimpeded Movement					
Child	0.34	2.25	**1.35**	0.75	**0.15**
Young Adult	0.71	2.61	**1.44**	0.58	**0.25**
Adult	0.67	2.75	**1.46**	0.59	**0.25**
Senior	0.40	2.42	**1.21**	0.48	**0.25**
Mobility-Limiting Impairment Profiles for Unimpeded Movement					
Cane	0.21	1.68	**0.91**	0.28	**0.35**
Crutches	0.35	1.22	**0.68**	0.34	**0.35**
Person Req. Assist	0.16	2.02	**0.98**	0.41	**0.40**
Walking Stick	0.14	1.68	**1.01**	0.41	**0.35**
Overweight and Obese Profiles for Unimpeded Movement					
Adult & Young Adult	0.60	2.32	**1.30**	0.54	**0.35**
Senior	0.46	2.11	**1.21**	0.63	**0.35**
Other Mobility-Limiting Profiles for Unimpeded Movement					
Oversize Luggage	0.08	2.62	**1.40**	0.55	**0.40**

[1] – Note that the maximum speeds differ from the SFPE foundational report [3] as outliers were removed

F.4 Demographic Distributions

To configure the comparative models using the previously defined agent profiles (Table F.1), the following table (Table F.2) outlines the demographic distributions assigned to each simulation. The total population for each simulation was set to 6250 people, which is half the capacity of the stadium. With the exception of Model 1 – the Current Default Parameters – the constructed models have adopted the agent profiles developed in the SFPE foundation study [3]. Models 2, 3 and 4 vary only by demographic distribution, meaning the characterized proportions of each population that is inputted to the software, which is described in further detail proceeding Table F.2. We do not do a gender breakdown of this data as of current there are concerns of subjectivity in that analysis though this data is available. The data can also be more subdivided by age groups, however some data sets lose their statistical significance when this is done.

All models speak to standard egress motivation principles, meaning that they are not reflective of emergency evacuations. These models serve to analyse the limitations of current modelling methods and highlight the importance of collecting and inputting more detailed data for practitioner use. Note that they are presented as an illustration of the impact that project-specific data input has on authenticating models with crowd simulation tools and are not meant for design validation purposes.

Table F.2: Demographic Distributions for Model Simulations.

Agent Profile	Model 1 (Default) Frequency		Model 2 (Average) Frequency		Model 3 (Observed) Frequency		Model 4 (Forecasted) Frequency	
Default Profiles								
Fruin Commuter	100%	6250	-	-	-	-	-	-
Total	100%	6250	0%	0	0%	0	0%	0
Able-Bodied Profiles								
Child	-	-	15%	938	15%	938	14%	875
Young Adult	-	-	25%	1563	15%	938	12%	750
Adult	-	-	35%	2188	25%	1563	11%	688
Senior	-	-	25%	1563	10%	625	3%	188
Total	0%	0	100%	6250	65%	4063	40%	2500
Mobility-Limiting Impairment Profiles								
Cane	-	-	-	-	0.06%	4	2.82%	176
Crutches	-	-	-	-	0.01%	1	0.47%	29
Req. Assist.	-	-	-	-	0.09%	6	4.19%	262
Walking Stick	-	-	-	-	0.03%	2	1.40%	87
Total	0%	0	0%	0	0.19%	12	8.87%	554
Overweight and Obese Profiles								
Adult	-	-	-	-	22.58%	1411	34.95%	2184
Senior	-	-	-	-	11.00%	688	14.95%	934
Total	0%	0	0%	0	33.58%	2099	49.90%	3119
Other Mobility-Limiting Profiles								
Oversize Luggage	-	-	-	-	1.23%	77	1.23%	77
Total	-	-	-	-	1.23%	77	1.23%	77
Combined Total	100%	6250	100%	6250	100%	6250	100%	6250

F.4.1 Model 1: Current Default Parameters

This model illustrates the functions and outputs of current modelling applications that rely solely on industry standard metrics. It is the simplest simulation of the composed models. This model does not include any project-specific data on the population – no data is manually inputted for demographic distributions, speed parameters, nor radii – and instead, it uses the pre-set default parameters of the software. This model uses the Fruin commuter profile and distribution.

F.4.2 Model 2: Manual Input Parameters for Average Population (Not Inclusive of Complex Profiles)

Like Model 1, this model does not consider the vast diversity of movement profiles and instead limits movement representation to that of able-bodied profiles. It is slightly more authentic however, as it is built using the profile parameters and demographic distributions that were observed at the stadium event, as opposed to relying on industry standard metrics. Data was thus manually inputted for the proportions of able-bodied profiles (children, young adults, adults, and seniors) that were observed at the stadium event.

F.4.3 Model 3: Manual Input Parameters for Observed Population

This model is the most authentic and sophisticated simulation presented in this study because it was configured to reflect the observed population at the event as accurately as possible.

It is therefore an improvement on Model 1 and Model 2 by including a diverse set of profiles, not limited by distribution curves nor average populations. In addition to the able-bodied profiles, parameters were manually inputted for mobility limiting impairments (cane, crutches, persons requiring assistance, walking stick), overweight and obese profiles (young adults and adults, seniors), and other mobility-limited cases (oversize luggage). The demographic distributions were assigned based on the population proportions that were observed at the stadium event. The observed distributions of the more complex profiles were assigned first, and then these proportions were subtracted from the respective able-bodied profiles according to age.

F.4.4 Model 4: Manual Input Parameters for Forecasted Population

This model was constructed as an additional piece to give insight to inclusive design forums. Otherwise known as universal designs, these are environments that are optimized to meet the needs of all people. Essentially, it would be an environment that is fully accessible and offers equal service, availability, and opportunity for all people, independent of any mobility limitations one may posses.

The manually inputted profile parameters are the same data as seen in Model 3. As an extension of this however, the demographic distributions are not reflective of the observed population at the stadium event but are rather defined by a variety of national demographic statistics provided by Statistics Canada [5] [6]. By aligning the crowd demographics with those of the Canadian population, this theoretical crowd simulates the ideal diversity that inclusive designs aim to achieve.

Like Model 3, the demographic distributions were first assigned to the more complex profiles based on their prevalence in the population, and then subtracted from the respective able-bodied profiles. The main parameters used to define these distributions were that studies found mobility-related impairments to affect 1.6% of Canadians from ages 15 to 24, 7.3% from ages 25 to 64, and 24.1% over the age of 65 [6]. In another study, obesity was also found to affect 54.96% of Canadians from ages 18-64, and 68.2% over the age of 65 [5].

F.5 Discussion

Using conventional crowd simulation software, each model was simulated 10 times, and the number of people egressed with time was recorded. The mean results were calculated for each model and graphed in Figure F.4. The mean percent population egressed with time is additionally provided in Table F.3. Note that the models are in the introductory phase and are subject to subsequent (albeit slight) modifications, and thus the outputs presented below are preliminary findings and are terminated prior to conclusion of the slowest moving individuals.

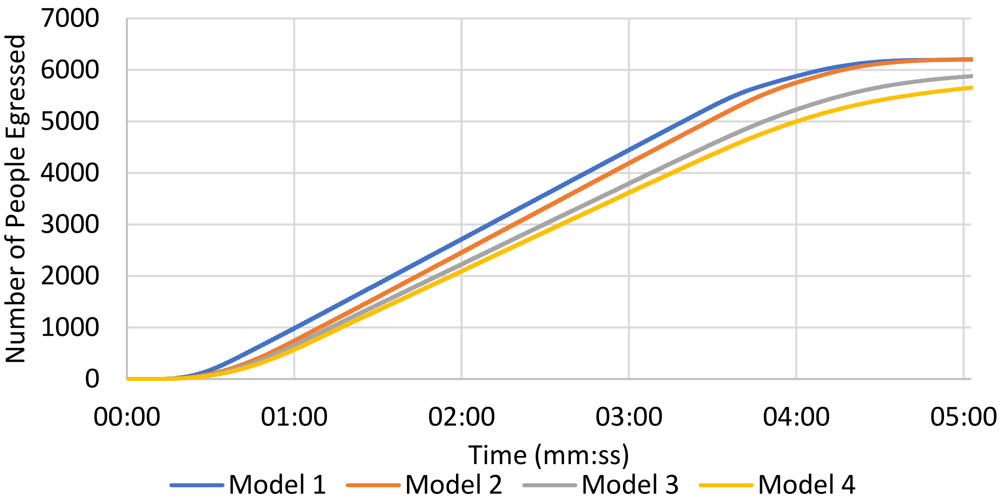

Figure F.4: Graph of the Mean Number of People Egressed with Time for All Models.

Table F.3: Mean Percent Population Egressed with Time for All Models.

Time (m:ss)	Percent Population Egressed			
	Model 1	Model 2	Model 3	Model 4
1:00	16%	12%	10%	9%
2:00	44%	40%	36%	34%
3:00	71%	67%	61%	58%
4:00	94%	92%	84%	80%
5:00	99%	99%	94%	90%

Model 1 shows the fastest egress, thus underrating the amount of time for the population to evacuate as the least accurate illustration of the evacuation. As anticipated, the overall time for egress increases as the demographic distributions are increasingly specified with each model. This is mainly due to the increasing proportions of profiles with reduced speeds and increased radii.

In comparison to Model 2, the accuracy of Model 1 at 3:00 minutes (3 minutes chosen as arbitrarily to compare the slope of each analysis where maximum percentage difference between the models were being observed- in future modelling all time stamps will be compared as the models are completed) is off by about 6%. This is because the mean speeds for able-bodied profiles are within the range of the default parameters, resulting in only a slight difference in egress time and observed behaviors.

Model 3 shows an even slower overall egress, along with unique pedestrian behaviors, based mainly on the fact that the newly introduced speed parameters are all slower, and the radii are greater. It is the most reflective model, considering it is based on real observations of the stadium crowds, and offers promising validation methods for design. Using project-specific details, this accurately reflects the expected population at the stadium. In comparison, the accuracy of Model 1 outputs at 3:00 minutes reduces by about 17%.

Model 4 shows the slowest overall egress, as the proportion of more complex profiles with slower speeds and greater radii increases drastically in comparison to the previous models. This shows the accuracy of Model 1 at 3:00 minutes is reduces by about 23%. This model highlights interest points in future stadium design, to better accommodate the vast population of persons with accessibility needs in Canada.

In conclusion, these calculations show how using the default parameters in Model 1 can severely underrate a required egress time. Although Model 1 shows strong results in comparison to the described distribution of average profiles in Model 2, this is not reflective of the many different movement capabilities observed in the present crowd illustrated by Model 3. Model 1 fails to acknowledge the more vulnerable portions of the population. Moreover, it is not a reliable method for simulating the demographic distributions seen in Canada's population in Model 4.

It is important to note that although this study presents ways to overcome some limitations of crowd modelling tools, additional research is still required to develop these tools further. Most notably, the presence of complex profiles is limited to those presented in Model 3 and 4, whereas there are many more profiles that would impact the functions and outputs of these models. This includes other mobility limiting impairments that are a result of psychological and physiological abnormalities such as cognitive deficiencies, mental health disorders, vision impairments, etc., and other movement behaviors that result from intoxication, cellular mobile usage, etc. This limitation is in part due to the lack of available movement data for the vast variety of profiles, and the inability of crowd simulation software to accurately incorporate said demographics. In addition to this, the crowd simulations presented in this study are defined by the architectural features of this stadium, meaning that these results and the impacts of relying on industry standard metrics would likely vary for a different environment. More specifically, this stadium consists of a relatively short travel distance in comparison to larger stadia. Therefore in other cases that the user is required to increase the travel distance, the size of the crowd, and/or the proportion of more complex profiles, the authors believe these will all contribute to increased egress times and different trends in human behavior.

F.6 Preliminary Conclusions And Future Research

The preliminary models introduced in this study show promising results and reliability for future modelling methods. Preliminary findings on the amount of people egressed with time highlight the limitations of using a single profile distribution, in comparison to increasingly authenticated models that incorporate project-specific details on observed populations. The models presented in this study bring attention to the prevalence of varying movement abilities and how excluding them can lead to inaccurate results. Instead, these profiles must be included in modelling methods to accurately depict the population at hand, and work towards creating inclusive designs. As being considered by the authors, the stadium profiles and model will require validation against observed egress for additional confidence. In addition to the overall evacuation performance, independent demographics in the simulations are being analysed in terms of mean, minimum and maximum times for egress to give further detail to their movement behaviors in the crowd this may be concurrently compared to actual egress data. Future research should also expand upon the degree of accessibility movement considerations, such as to diversify available datasets to the inclusion of profiles with psychological abnormalities, other physiological abnormalities, intoxication, and mobile usage, to name a few. Further anthropometry effects should be considered as reviewed in the SFPE Foundation report. Lastly, a range of crowd modelling software typically used in stadium design should be considered.

Acknowledgements

Human Behavior and Evacuation Skills Team, and the Accessible Environments Team within Arup; Lund University for preliminary technical discussions; and the SFPE foundation.

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Appendix G: Fire Evacuation And Exit Design Strategies For Cultural Centres

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Abstract

A three year study was undertaken in a newly renovated Canadian cultural centre (a heritage building museum), were it was identified that special events and services now being offered to the public have changed the typical flow pattern and density of visitors within the floor area of the building. To understand the unique challenges in this heritage building and acquire specific data addressing human performance based on demographics and group behavioural trends, a qualitative analysis of one unplanned (accidental) evacuation incident with approximately 1,700 occupants, and a quantitative and qualitative analysis of a planned and un-announced evacuation with 460 occupants was performed by reviewing recorded CCTV footage. For the planned event (in 2016), a questionnaire was also provided to the staff and some visitors, to obtain additional information and insight on the event. This was also used to evaluate the employee behaviour against those set out in the building's emergency response plan. A follow-up planned evacuation of the building occurred one year later (2017) than the aforementioned events. The purpose of that event was to analyze changes that were implemented in the overall evacuation strategy. These changes focused on the organization of designated staff and the adoption of improved egress and exit signage. Herein, the goal of the study is to utilize the results to develop a baseline and a better understanding of the observed behaviours. This includes gaining insight

into the decision-making process and actions of people during the pre-evacuation and travel phases (evacuation phase) of emergency egress situations. Findings from the study are intended to inform the development of evacuation modelling tools which can more accurately represent the behavioural patterns observed.

G.1 Introduction

Modern codes and standards all consider an occupancy factor when determining the design requirements of a building. The occupancy type can have an effect on the design parameters for the means of egress and type of exit system used. The type of exit system and the dimensions for these facilities, their number and location, fire separation from the rest of the building, as well as exit signs and emergency lighting are all correlated to the use of the building and occupant load. Although occupancy classifications are based on assumed fire loads[1], the number of occupants, and the ability and needs of occupants to evacuate, they may not fully account for the occupants' tendencies and behaviour during a fire evacuation. For example, in buildings such as cultural centres, where the use or occupancy is intended for the gathering of persons for civic, political, travel, religious, social, educational, recreational or like purposes [1],designers may need to consider high occupant loads and density variations, demographic variation (age, nationality, mobility or sensory impairments etc.), the intelligibility of the voice communication message and alarms in a large and noisy space, the unfamiliarity of occupants with: the building layout, local language, egress path identification, the collective behaviour of small groups of people in a crowd and the presence of trained staff providing assistance, to truly understand if we are achieving a safe building design and not one that is simply code compliant. [2, 3 4]

In order to properly account for these factors when undertaking a building design, the designer or architect would have to understand how the aforementioned elements interact and influence the decision process during a fire evacuation. Unfortunately, there is lack of data which can inform such a strategy for high occupancy cultural buildings, particularly where vulnerable populations and unique cultural differences conjugate in masses. [3, 4, 5, 6]

Alternative solutions, in a Canadian context, are founded on a performance-based approach and are being used more frequently to address constraints in existing cultural centres that, by their very nature can be complicated to retrofit. These solutions are typically approached through a performance-based design that often require quantification of both ASET (Available Safe Egress Time - the time before conditions become untenable) and RSET (Required Safe Egress Time - the time for the population to get to a place of safety, as represented by the required safe egress time) [2, 4, 6, 7]. This approach has been established by several authorities and code committees to be an acceptable method to demonstrate that a reasonable level of safety has been achieved to meet the intent, objectives and functional statements of the applicable code [3]. The RSET can be calculated manually; however, the application of evacuation simulation software is being used more frequently to enable the designer to incorporate the values obtained in their design fire scenarios and to process several scenarios and iterations quickly and efficiently. Despite having a plethora of tools available, that include manual calculations and evacuation simulation software, it is still imperative to understand the building's occupants so that engineering and emergency procedural designs and methods more accurately reflect realistic occupant behaviour during an emergency or fire events and not simply their movement tendencies (speed and direction) [8]. Furthermore, this would allow for the development of more representative computational tools that accurately represent the expected behaviour of individuals while considering how they interact with various groupings or other individuals.

While the study could have focused on documenting the different stages of the RSET for a diverse population in a cultural centre and simply document speed and time, the authors are more interested in demonstrating the correlation that exists with existing behavioural decision theories, such as the Protective Action Decision Model (PADM) [2, 3, 4, 9]. In theory, the combination of both approaches could be used to create a more accurate and realistic representation of human behaviour in evacuation models.

G.2 Motivation And Background

Special events such as a monthly night club, weddings, receptions, birthdays and conferences were now permitted and being offered to the general public as new revenue generating services for the subject Cultural Centre building herein (principally a heritage structure and museum). These new events have changed the typical flow pattern and density of visitors in the building from those originally designed and considered for a cultural centre. More specifically, this allowed for larger concentration of occupants isolated to one specific room or floor space with limited or restrained access to every available exit in the building.

Two specific events that occurred in 2016 raised concerns with the building staff and their executive as to the safety of the visitors. These events were full evacuations. The first event, occurring in autumn, was the activation of a manual station by a night club patron. The patron had wanted to "smoke" without having to leave the building. Limited information is available for this event; however, the executive modified several of their strategies and increased security staff to address some of the gaps identified during this incident. The second event, which was recorded on CCTV cameras and provided to the authors for use in the study, was a fire alarm initiated from the activation of a manual station by a child in the west vestibule area of the main entrance. This incident occurred on a Saturday around 16:00 in the afternoon early autumn. For an unexplained reason, the fire alarm system transferred to the 2nd stage within 2 minutes and 18 seconds of the initial alarm being activated and resulted in a complete evacuation of the building. Approximately 1,700 visitors were present at the time of the alarm. Upon activation of the second stage alarm, the elevators were recalled to the ground floor, the air handling units shutdown, some of the smoke evacuation fans started and the eight accordion type horizontal sliding fire doors (called WON-Doors herein) released and closed the access to the atrium from the wings and hall at each floor level. The activation of the WON-Doors created an unforeseen challenge as neither the security staff nor the visitors appeared to know what they should do and how to exit the floor area once the main entrance to the floor area was blocked. Once the visitors gained access to the atrium area, as it appeared as though they figured that these doors could be opened manually by them, they were all directed to exit the building through the main entrance, where the alarm was activated.

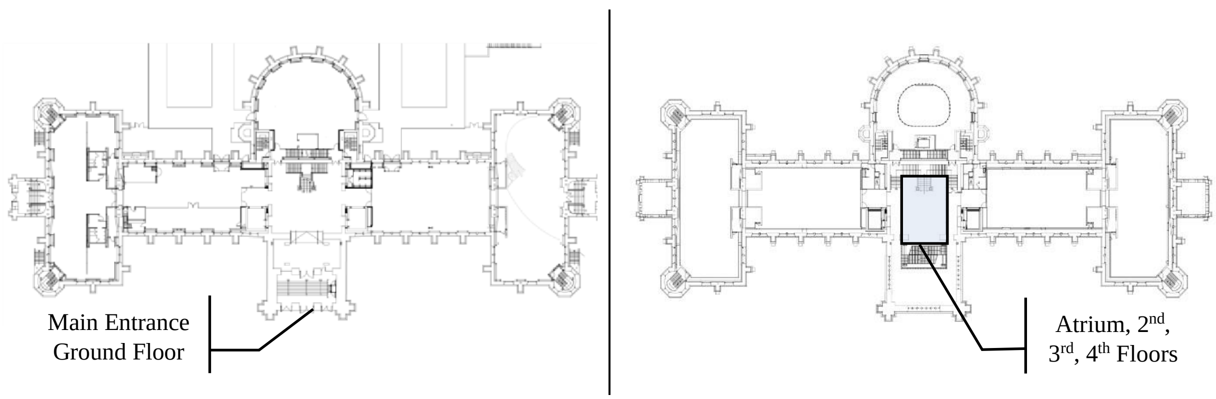

Figure G.1: Ground Floor and 2nd, 3rd and 4th Floor General Layout

As a result of the events mentioned above, the building executive and protection office wanted to know what variables, be it physical or administrative, specifically affected the evacuation of visitors. In order to do so, they had decided to undertake a full-scale unannounced evacuation with the underlining objectives of evaluating the behaviour of staff and provide quantifiable data to improve the building's overall fire safety and evacuation strategy. Based on the adopted changes (primarily improved signage and staff training) that were implemented after the initial evacuation in 2016, a subsequent annual (mandatory) evacuation was performed in 2017 to assess the effectiveness of the implemented physical and administrative modifications. The CCTV footage of both planned evacuations were shared with the authors to permit an overarching human behaviour in fire study and to utilise the results to develop a baseline and a better understanding of the observed behaviour, decision-making process of participants and specific (including unexpected) actions of people during the pre-evacuation and travel phases (evacuation phase) of emergency egress situations.

G.3 Methodology Of Data Collection

The building's exit facilities, evacuation procedures and strategies were reviewed prior to performing the pre-planned and unannounced evacuation in 2016. The authors conducted a comprehensive survey of the evacuation routes and exit facilities with specific focus on the following conditions: clearly marked and well lit; wide enough to accommodate the number of evacuating personnel; unobstructed and clear of debris; and unlikely to expose evacuating occupants to additional hazards. The building's emergency response plans and posted emergency evacuation plans, which include a primary and secondary path of travel, were also reviewed. This allowed the authors to gain an understanding of the staff's roles and responsibilities during an evacuation and the desired behavioural responses from occupants. The information contained within these documents would be used by the authors to compare the expected behaviours with those witnessed during the evacuation. A comprehensive review of the closed-circuit television (CCTV) cameras was also performed prior to the evacuation to determine the angle of view and sight lines that would permit the best overall coverage of each floor area and to decipher individuals and group behaviour for the authors use. Four of the CCTV cameras were malfunctioning during the time of the exercise and this resulted in some areas on the floors having little to no coverage. For example, the central core of the building, above the 1st floor had no camera coverage.

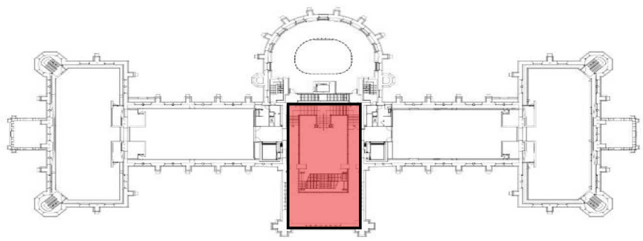

Figure G.2: Central Core of the Building with no CCTV Coverage

G.4 1st Planned Annual Evacuation - Autumn 2016

A planned and unannounced evacuation (drill) was conducted on a Thursday evening in the autumn of 2016. Thursdays are typically the busiest days of the week as free admission is provided after 16:00. Apart from the building's executive staff and Chief of Protection, no one was told of the evacuation. The visitors, the security guards and building staff on site, were not aware of the planned evacuation. It was a cold evening on the day of the evacuation with a temperature of -1^{o}C (30.2^{o}F) and unexpected snow flurries occurred.

Data was extracted from 448 minutes of video footage provided through 47 closed circuit television (CCTV) cameras. In context, as there are limited automatic tools available for data extraction of videos, and the extraction is highly dependent on the quality of the footage for (potential) AI algorithm extraction, the necessitated person-hours to extract relevant data were approximately 260 hours of manual postprocessing. A systematic review of the CCTV footage was performed to account for every individual in the building post-event. Every occupant that exited the building was accounted for through a thorough analysis of the CCTV footage available at each exterior exit. This procedure necessitates tracking people through multiple cameras. For example, one person may be tracked through the structure by six separate cameras to build the appropriate timeline. Hence the process of recording movement in this fashion is time consuming and the authors limited the data extraction in this detail to one event only.

Figure G.3: CCTV Footage Demonstrating Film Quality and Exit Use During the Autumn 2016 Evacuation

In total, information on 347 of the 458 occupants witnessed at the autumn 2016 evacuation was collected. Data was collected for every occupant that was observed on a floor area during the 1st stage alarm and seen leaving the building by one of the exits. The CCTV footage was also reviewed to provide insight on the behaviour of visitors and staff and compare them to the behavioural statements that have been identified and linked to one of the five stages of the Protective Action Decision Model (PADM), which will be presented by the authors in future publications in more detail [2, 3, 4, 9]. For the planned event (in 2016), a questionnaire was also provided to the staff, and some visitors, to obtain additional information and insight on the event. This was also used to evaluate the employee behaviour against those set out in the building's emergency response plan. Staff behaviour is beyond the scope of this paper, the current focus of this paper is simply to introduce the research study of the occupant behaviour for provisional feedback from the fire safety community.

The following statements demonstrate how the authors made decisions to interpret movement / associations and the relevance of specific data collected. Behavioural and demographic data was broken down in the following categories. Every tracked occupant was assigned an Agent number that represented the floor and the location (wing or hall) where they were located at the moment when the 2nd stage alarm was activated. Each occupant was then tabulated based on their physical location on the floor or in order of evacuation from the floor area. To determine the effects of Age, occupants were broken into five separate age categories (under 3 "Tiny Tots", 3-12 "Kids", 13-17 "Teenagers", 18-65 "Adults", over 65 "Seniors"). These categories were selected to match those being used by the buildings marketing database. For example, every occupant identified as a "tiny tot" was seen in a stroller, in a carrier, or very small and walking in a limited capacity during the period of time between 1st and 2nd stage alarms. A limited capacity was defined as requiring assistance (hand holding) or holding on to objects or propping themselves up for a brief period.

When the 2nd stage alarm was initiated the "tiny tots" that were initially identified were re-classified as a child (3-12) if they were observed leaving the building on their own accord and capable of dressing themselves (putting on their jackets and tuques). The occupants were identified as being Part of a group or traveling alone to study Group travelling. Grouped occupants were identified during the period between 1st and 2nd stage alarms if they were moving in general proximity of each other, held hands, were seen to make visual contact and communicated to one another. Every group of occupants was re-evaluated during the pre-evacuation phase and the travel phase once the 2nd stage alarm was initiated. The occupants that tended to migrate closer together when the alarm was initiated, traveled at the same velocity, were in visual contact with one another and communicated quite frequently to each other during the response period were maintained as a group. Those occupants that failed to exhibit these traits were reclassified and excluded from a specific group. Cultural background/mobility impairments were considered when possible. A detailed description of each occupant was provided that included such features as race or ethnicity, hair style and colour, clothing, mobility impairments or accessories. The intent was to identify specific features that visually defined an occupant and would make them easily identifiable by someone else reviewing the footage. In some cases, the specific feature, like a walker or a cane could cause a change in evacuation behaviour. The race or ethnic background was identified by way of recognizing visual features common to a certain racial or ethnic group. It cannot be determined with certainty what ethnic or cultural background participants belong to due to individual differences and factors not visually apparent. It was apparent in the analysis that this was difficult to assess and therefore the authors have followed this aspect with a separate study and prepared a paper that is provided in the Interflam proceedings [10]. The pre-evacuation time was calculated as being the time from when the 2nd stage alarm was activated to when it was 'visually apparent' that the occupant decided to evacuate. Visually apparent was determined to mean that there was an obvious twist of the head resulting in the body shifting from its original position to one leading the occupant in the direction of the exit. Where the head could not be seen, the time was registered when it was seen that the body was twisting and that a first step was taken in the direction of the exit [11]. The 2nd stage alarm was considered as the preliminary cue to evacuate as there was a change in tones from a single chime every three seconds to a consistent bell tone. The total evacuation time was taken as the time taken by the occupant from the initial cue to the moment in time where they were physically seen at the exterior of the building. Lastly, during evaluation of the CCTV footage, the authors considered identifying specific behaviours or individual characteristics that resulted in a delayed response or a shift in response. Where possible, general observations were made when specific actions or events were noticed. The underlying objective for this part of the study, was to demonstrate the accuracy of or identify gaps in the behavioural theories that have been identified and linked to one of the five stages of the Protective Action Decision Model (PADM) [2, 3, 4, 9].

G.5 2nd Planned Annual Evacuation - Autumn 2017

A second planned and unannounced evacuation was conducted on a Thursday evening in the autumn of 2017. Unlike the day of the evacuation in 2016, the evening was clear and the temperature was 9^{o}C (48.2^{o}F). The purpose of the event was to provide the executive management and security officer the opportunity to evaluate changes in the emergency response plans adopted one year later. These modifications focused on the organization of designated staff and the adoption of improved egress and exit signage. These measures were identified as areas of concern following the evacuation and the incidents of 2016. This allowed the authors a unique advantage to study the effectiveness of the implemented strategies. The condition and planning of the evacuation was conducted in the same manner as before (staff and visitors were uniformed for example). Subsequently this event's CCTV footage was provided to the authors for analysis however, it was not analyzed to the degree observed in the aforementioned event in 2016. The analysis was focused on examining the effects that the administrative and physical modifications implemented after the initial evacuation had on the occupant flow and exit selection. The primary findings will be discussed in the observation and discussion section of the text.

G.6 Evacuation Modelling

Both the qualitative and quantitative data collected was used to create an agent profile database that can be used in evacuation modelling software and to recreate the pre-planned, unannounced evacuation for validation and verification efforts. This can be part of the quantitative validation process to understand the capabilities and limitations of any software using these predefined agent profiles as they pertain to the recorded pedestrian behaviour. The preliminary set up of the modelling exercise is a discussion in the future work section of this paper. An extensive site survey of exhibit locations and measurements during 2016-2017 has been undertaken for this task. Modelling is currently beyond the scope to critically analyse herein but is a subject of the authors' future research. Hence, we do not provide the total evacuation times and preliminary times observed herein.

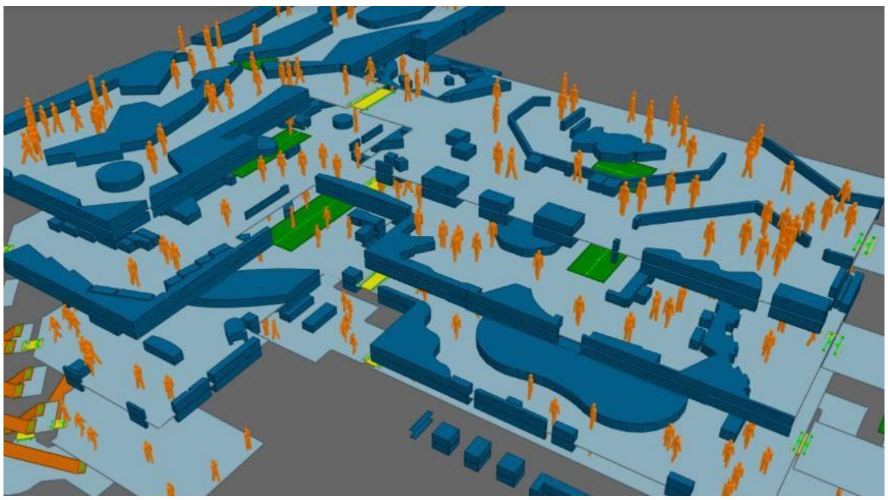

Figure G.4: Rendered Modelling Space for Museum with Exhibit Configuration as Surveyed in A Utilised MassMotion Environment

G.7 Observations And Discussion

It is through the qualitative and quantitative analysis of the two planned evacuations that the authors can clearly state that building features, such as exit location and visibility, staff and outside climactic conditions play a large role in the way occupants behave during the pre-evacuation and travel periods. The following section looks at some of the key factors that appeared to influence occupant's decision or ability to evacuate. Our current analysis presented herein is limited only to the observations taken for the planned events. The unplanned event will be presented in future work.

G.7.1 The effects of Age and Accessibility

The age of each occupant appeared to have some influence on the behaviour of other occupants and resulted in slower evacuation times observed. Several parents who were accompanied by Tiny Tots were noticed to leave the immediate floor area with a stroller, when it is noted in the building's emergency response plan that strollers are to remain in place at the freight elevator lobby during an emergency evacuation. This behaviour hindered the flow of egress as two people are required to lift the stroller down stairs (which occurred). A number of the senior occupants were seen using handrails to walk down the stairs, some required direct assistance, or some carried on slowly due to an identified (cane, limp), and in some cases unidentified, mobility impairment. Several parents were also seen carrying their children (Child) in their arms and then using a handrail to steady themselves when negotiating stairwells. In all, approximately 20% of the building's occupants in the 2016 evacuation required assistance or had their mobility impaired in one shape or form by a physical object or by another occupant. Table G.1 lists the populations age categories observed in the first planned evacuation and their respective average evacuation times.

Table G.1: 2016 Evacuation Occupant Population by Age Category

Age Category	*Age*	*No. of Occupants*	*Percentage of Occupants (%)*	*Average Evacuation Time (hr:min:sec)*
Tiny Tot	0-2	16	5	0:04:29
Child	3-12	48	14	0:03:34
Youth	13-17	18	5	0:03:29
Adult	18 - 65	252	73	0:03:13
Senior	65 +	13	4	0:03:22

G.7.2 Group Travelling

The authors investigated if there was a correlation between the pre-evacuation times, as seen in Table G.2 and the fact that occupants were traveling in groups. Although 95% of the occupants were seen traveling in groups of 2 to 9, no direct correlation was able to be determined from the group size and the pre-evacuation times recorded. It was clear, on the other hand, that a hierarchy exists within each group. It was observed, on the basis of the recorded data, that the recorded groups do not move until a specific person initiates movement. Cultural differences seemed to have an effect on this group hierarchy as in some identified ethnicities the most senior member was looked upon as this figure and in others, it was the male. It was observed that children, upon hearing the 2nd stage alarm would go to their parents or grandparents, tell them something and wait for them to make a decision before reacting. Exact quantifications of occurrences will appear in future work.

Table G.2: Autumn 2016 Evacuation Recorded Pre-Evacuation Times.

Pre-Evacuation Time (seconds)	*No. of Occupants*	*Percentage of Occupants (%)*
0-5	35	17
6-10	36	18
11-20	30	15
21-30	38	19
31 - 60	40	20
61 - 120	18	9
121 - 210	7	3

G.7.3 Exit Contribution and Comparison

A systematic review of the CCTV footage was performed to account for every individual in the building. Every occupant that exited the building was accounted for from the CCTV footage available at each exterior exit. The following table demonstrates the distribution of occupants by exit facility and the percentage that each facility contributed during the evacuation. An analysis was performed on the effects that the administrative and physical modifications implemented after the initial evacuation had on the occupant flow and exit selection between both planned evacuations. Table G.3 below shows the exit facility contribution for each of the planned evacuation.

Table G.3: Exit Facility Contribution Evacuation Event comparison (2016 vs 2017)

Exit Reviewed	*Autumn, 2016*		*Autumn, 2017*	
	Occupants	*%*	*Occupants*	*%*
Café Exit - Exit Door (East Terrace)	0	0	55	14.2
Main Entrance	422	92.3	132	34.2
Stairwell 10 - Group Entrance Exit (East)	- [a]	-	24	6.2
Stairwell A - Exit Door (South/East)	0	0.0	9	2.3
Stairwell B - Exit Door (North/East)	0	0.0	44	11.4
Stairwell C - Exit Door (South/West)	10	2.2	5	1.3
Stairwell D - Exit Door (North/West)	13	2.8	10	2.6
Stairwell E - Exit Door (East)	6	1.3	0	0
Stairwell F - Exit Door (West)	6	1.3	0 [b]	[b]
West Hall Vestibule Exit Door (Terrace)	0	0.0	107 [b]	27.7
TOTAL / OVERALL	**457**		**386**	

[a] The occupancy and exit contribution could not be tracked through stairwell #10 – group entrance doors as the camera footage jumps by 3 to 5 seconds in random intervals.

[b] The exit contribution of the West Hall Vestibule was combined with Stairwell F as they both merge together outside.

Approximately 92 % of the visitors during the autumn 2016 evacuation exited the building through the main entrance on the 1st floor instead of using one of the six available exit doors nearest to them on the floor space. The modern North American building codes (NFPA and IBC), particularly in Canada, specifically state that if more than one exit is required in a building, every exit shall be considered as contributing not more than one half of the required exit width, including the principal entrances serving a dance hall or a licensed beverage establishment. 1 The intent behind these requirements is to limit the probability that an excessive portion of the exit capacity will be concentrated at one location, which could lead to delays in the evacuation to a safe place.1 The inclement weather (-1^{o}C and snow) during the 2016 evacuation influenced the behaviour of the majority of the occupants and resulted in higher than anticipated evacuation times due to an unwillingness to go outside and a need to gather belongings in a cloak room located on the 1st floor near the main entrance. The cloakroom remained accessible to the public during the 2017 evacuation however, it is hypothesized by the authors that this was not a gathering point as the weather was fairly mild. In the 2016 event, the eight accordion type horizontal sliding fire doors (WON-Doors) did not activate to close access to the atrium on the floor areas, which permitted access to the main entrance on the 1st floor. All WON-Doors except for one initially activated during the evacuation in 2017 and created a physical barrier between each of the floor areas and the atrium. Combined with the new "green running man" exit signs installed on the both sides of the WON-Doors and clear direction from security staff on each floor area, it appeared to assist the occupants' decision making as no one tried to open the WONDoors, as was the case in the first evacuation 2016 incident to gain access to the atrium to exit through the main entrance.

G.8 Preliminary Conclusions And Future Research

An empirical data set was created from the pre-planned and unannounced evacuation in the autumn of 2016. This included data pertaining to each individual's age group, sex, race or ethnicity, if the individual was travelling as part of a group or not, specific location on the floor space, time when reacted to the alarm, specific features like a walker, cane or stroller that could cause a change in evacuation behaviour and their total evacuation time.

The data set created as a part of this study for the pre-planned and unannounced evacuation will help to develop a baseline for the behaviour and actions of people during the pre-evacuation and travel phases of emergency evacuation situations, and it will aid the fire safety engineering community with the decision process for egress and evacuation strategies.

The authors' data was used to create agent movement profiles for use in evacuation modelling software to allow verification and validation against a recreation of the first pre-planned and unannounced evacuation. This can be part of the quantitative validation process to understand the benefits, capabilities and limitations of any evacuation software using predefined agent profiles as they pertain to the behaviour of the visitors – particularly to represent group behaviour [12]. In order to specify procedures that were lacking in a modelling software, the data can be used to create new features to represent group behaviour, appropriation and authoritative action/response. It is the authors' intention to utilise these procedures for future research to validate, verify, and create different evacuation scenarios to optimize the desired outcome based on fire alarm sequence of operation in similar buildings to create adaptive scenario/situation recognition and reactions by each agent based on the parameters defined.

It is clear through the qualitative and quantitative analysis of two evacuations that building features, staff and climactic conditions outside play a large role in the way occupants behave during the pre-evacuation and travel periods. The PADM, currently including the 28 Behavioural Statements and the five stages, as seen in references [2, 3, 4, 9], seem to hold true in the evacuations seen by the authors, though should be intensely interrogated in future manuscripts. Nonetheless, some new insight and further studies should be considered to look at how cultural differences, age, the size of groups and the use of cellular phones can affect decision making in an evacuation.

Without understanding how people behave and react, we will continue having difficulties optimizing the exit configurations and evacuation strategies to achieve the desired result: an orderly and safe evacuation, not simply one that is code compliant [2, 4].

It is clear that a solution to the challenge presented by human behaviour in an evacuation will not be solved in the near future. If this study can demonstrate one thing, it is that empirical data is complicated to gather, time consuming, expensive and subject to the interpretation of the individual reviewing it. There is a lack of specific data available to the fire safety engineering community that could assist in better understanding the limitations of the software we are using to demonstrate that a building is safe for the occupants. That being said, the PADM developed thus far, including ongoing reviews by the Human Behaviour in Fire (HBIF) community, will only future assist researchers with collecting empirical data that is relevant to the decision process for determining the safety of our buildings and optimizing evacuation strategies.

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