AI-BASED CYCLIST SAFETY HYBRID MODELLING FOR FUTURE TRANSPORT NETWORK

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Abstract

A cyclist is a vulnerable road user whose safety is affected by several externalities. The global aim of the research is to investigate the effect of critically identified variables of rider attributes of age, gender, varied environmental condition of lighting, meteorology, and micro-infrastructure variables on the safe usage of the infrastructure for a cyclist. Presently, very few works have attempted to undertake such modelling. A novel methodological framework is developed, consisting of descriptive, statistical, artificial intelligence and mathematical approaches. Accurate prediction models are developed, and in-depth knowledge of how different variables affect cyclist safety are identified, modelled, and quantified. It is found that the variables of age, gender, varied environmental conditions, and micro-infrastructure variable are critical variables affecting the safe usage of infrastructure. These variables, both individually and in combination, impact cyclist safety. Cycling safety is a dynamic variable that varies temporally and spatially. The spatial and environmental variables have a significantly varied effect on safety depending upon the rider personal attribute. As the number of safety variables that the cyclist must conform to grows, so does the risk. The riskiest environmental conditions are exacerbated by the prevailing traffic flow regime, posing a significant safety risk to cyclists. The modelling requirement of a cyclist is significantly different from motorists. A hybrid intelligent modelling paradigm is required, as demonstrated in this research. The study results can significantly impact the route choice, modelling, and planning of infrastructure. A shift in the road safety analysis towards nanoscopic modelling can help achieve zero-vision road traffic fatality. The research reinforces a need for planning and design of infrastructure to move towards a more holistic approach while considering the limitations of this vulnerable road user.

List of publications

	Title	Contribution
	Conferences	
1.	International Road Federation-YP Summit September, 2020	Paper presented
2.	Swiss Mobility Conference 2020	Paper presented
3.	21st International Conference on Intelligent Data Engineering and Automated Learning - IDEAL 2020, Portugal	Paper presented
4.	3rd International Conference on Emerging Trends in Electrical, Electronic and Communications Engineering (ELECOM), Mauritius, 2020	Paper presented
5.	Symposium Reforming Multi-Disciplinary Engineering Innovation for the New Normal-Northumbria University, 2020	Paper presented
6.	6th International Symposium on Environment-Friendly Energies and Applications (EFEA), 2021	Paper presented
7.	53rd Annual Universities' Transport Study Group (UTSG) conference, 2021	Paper presented
8.	19th Annual Transport Practitioners' Meeting, 2021	Paper presented
9.	7th International IEEE Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS 2021)	Paper presented
10.	18th International Road Federation (IRF) World Meeting & Exhibition, 2021	Paper presented
11.	9th International Cycling Safety Conference (ICSC), 2021	Paper presented
	Journal Publications	
1.	Intelligent nanoscopic safety cyclist modelling for variable environmental conditions	IEEE Transactions on Intelligent Transportation Systems

2.	Deep Neural Network-based hybrid modelling for development of the Cyclist Infrastructure safety model	Journal of Neural Computing and Application
3.	Intelligent modelling of Personal Attribute and Road Environment conditions for riskiest cyclists infrastructure type prediction	IEEE Access (minor revisions submitted)
4.	Real-Time Nanoscopic Rider Safety System for Smart and Green Mobility Based upon Varied Infrastructure Parameters	Future Internet
5.	Intelligent real-time modelling of rider attributes for the last mile delivery to provide mobility as a service for future transportation systems	Applied Science
6.	Using Deep learning to construct a real-time Road Safety model; modelling the personal attributes for cyclist.	Lecture Notes in Computer Science (LNCS)
	Awards and Invited Speakers	
1.	Keynote speaker on traffic management workshop by Central University Kashmir, April 2021	Research dissemination and contribution towards society
2.	International Road Federation- Young Professionals Summit September 2020	Invited keynote speaker.
3.	Northumbria Community Impact award, 2020	Research dissemination and contribution towards society
4.	Northumbria Empowerment Award, 2020.	Research dissemination and contribution towards society

Table of contents

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Declaration

I declare that the work contained in this thesis has not been submitted for any other award and that it is all my own work. I also confirm that this work fully acknowledges opinions, ideas and contributions from the work of others.

Any ethical clearance for the research presented in this thesis has been approved. Approval has been sought and granted by the Faculty Ethics Committee on 24/11/2019 2020, ETHICS online Reference No. 20731).

I declare that the Word Count of this Thesis is 52,729 words.

Name: Faheem Ahmed Malik

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Date: 30/07/2021

List of Abbreviations

AI: Artificial Intelligence

ANOVA: Analysis of Varience

A_R : Area

A_T: Type of Association

AUROC: Area under the ROC curve

C: Crash frequency

C.I: Confidence Interval

C_M: Crashes per million miles

C_R: Crash Rate

D_f: Degree of freedom

D: Dual Carriageway

f: Frequency

f_e: Expected value

f_o: Observed value

FHWA: Federal HighWay Administration

F_L: Flow

F_{LR}: Flow rate

H: Hypothesis adopted

H_0: Null hypothesis

H_1: Alternate hypothesis

I: Importance

KMO: Kaiser Meyer Olkin

L_B = Lower bound,

L_L: Lower Limit

L_S: Levene statistic

M_{AG}: Mean age difference

M: Medium

mm: Millimetres

M_P: Miles per person

M_R: Miles rate

M_T: Total million miles traversed

M_{MF}: Male/Female ratio

n/a: Not Applicable

n/o: No association

N_R: Normalized risk

N_p: Normalised Importance

NTS: National Travel Survey

O: One way street

p: Probability

P: Population in millions

PCA: Principal Component Analysis

R_{HL}: Change in the road hierarchy

ROC: Receiver Operating Characteristic

RN_G: Normalised risk per group

RN_O: Overall normalised risk

R_R: Relative risk

R: Roundabout

S: Small

SPSS: Statistical Package for the Social Sciences

S: Single Carriageway

S_L: Slip Road

TADU: Traffic And Data Unit

TfL: Transport for London

T_M: Total miles traversed

T_{MF}: Male/Female ratio of trips per person

T_P: Trips per person

T_R: Trips rate

TRADS: TRAffic flow Database System

TRL: Transport Research Laboratory

U_B = upper bound

U_L: Upper Limit

UTMC: Urban transport management centre

V: Cramer V

Chapter 1.

Introduction

1.1. Background

The promotion of cycling as a mode of travel has social, economic, and environmental benefits. In effect, in recent years, cycling has gained a more prominent role in transportation policy because of its pivotal role in providing a sustainable mode of travel. To achieve an overall sustainable transport system, cycling mode share has to increase by many folds (Bell CBE *et al.*, 2016). It can reduce energy consumption and enhance the liveability of the cities. However, there are concerns regarding road safety, which is the most commonly perceived barrier to its uptake (Aldred and Crosweller, 2015; Lawson, 2015). The identification of the physical and environmental threats to the cyclist in the natural urban environment provides an insight into the preference and choice of the cyclists (Lawson, 2015).

Creating a complete and comprehensive network for cycle traffic is imperative, which is both comfortable and attractive (Parkin, 2018). Road traffic crashes have adverse effects on human health, the well-being of individuals, and society. Crashes have associated pain, grief and suffering due to personal injuries, property damage, increased travel time, and a corresponding increase in carbon emissions due to congestion. Road safety involves a complex interaction of factors and underlying phenomena, requiring an in-depth understanding and knowledge-driven measures to reduce crash frequency and impact. The preferences and requirements of cyclists are different from other road users (Laureshyn *et al.*, 2017). Safety is also a significant mode and route choice variable (Akgun *et al.*, 2018). The effect of safety pessimisticism is a more considerable deterrent than the effort involved in riding (Wardman, Hatfield and Page, 1997). The susceptibility of the cyclists towards different externalities is more pronounced than the motorists (see (Zhang *et al.*, 2000; Theofilatos, Graham and Yannis, 2012; Bella and Calvi, 2013)). These externalities include different infrastructure types, personal attributes of the rider, traffic flow regime, variable weather, and lighting conditions. Presently, there is insufficient evidence to understand the relationship between these variables and safety for a cyclist (TRL, 2011).

An intelligent transport system should focus on transferring people from a particular origin to a given destination in the shortest possible time and aspire to enhance rider safety and quality. A well-designed cycling network should accommodate cyclists of different abilities plying at different speeds. There exists a positive relationship between the index of infrastructure accessibility and cycling modal share. Numerous studies have attributed seven significant risk types for a cyclist (Delen, Sharda and Bessonov, 2006; Kim *et al.*, 2007; Abdulhafedh, 2017):

a) Driver behaviour,
b) Vehicle factors,
c) Roadway characteristics,
d) Traffic volume,
e) Speed,
f) Time, and

g) Environmental variables.

The work on the perceived risk and mode choice by (Noland, 1995) led him to conclude that the mode shift occurs when risk perception for a given mode is reduced. Concerning safety improvements, he concluded that the mode shift elasticity for improvement is greater than 1, i.e. cycle safety improvements attract proportionally more people to use this mode for commuting. However, Meade and Stewart, (2015) argued that an increase in the cycling casualty could occur if the safety concerns are not addressed, and a corresponding increase in mode share occurs.

The effect of risks of cycling in a typical urban environment is a more significant deterrent than the effort involved in cycling (Wardman, Hatfield and Page, 1997). There is a positive relationship between cycling mode share and road safety satisfaction (Meade and Stewart, 2015). A stated preference (Wardman, Hatfield and Page, 1997) model for cycling modal shift concluded that it is essential to improve the cyclist's safety to achieve a modal shift towards cycling. This can only be achieved if cycling is made safe, convenient and feasible for all ages across the gender (Pucher and Buehler, 2008). Short & Caulfield 2014, while studying the safety challenges of increased cycling in Ireland concluded that cyclist is 40 times more likely to be killed or injured in a collision than the motorists and eight times for being involved in a fatal collision for every kilometre (Short and Caulfield, 2014). Therefore, it is imperative that cycling as a mode is made safer to reduce the number of crashes and make it a more attractive mode of travel and increase its mode share.

The preferences and requirements of cyclists are different from other road users (Laureshyn *et al.*, 2017). Cyclist considers safety, pleasure and a smooth road surface to be the most essential features of the link (Guthrie, Davies, D and Gardner, 2001).

Although there is a negative relationship between cycling commuting and distance, using merely journey time as a postulation in mode choice modelling is incorrect. Cycling time spent in various conditions is a critical variable with implications for mode and route selection (Wardman, Hatfield and Page, 1997).

1.2. Motivation of study

There were 1,870 fatalities, 25,950 seriously injured, and 129,810 slight injuries due to road traffic crash in Great Britain in 2019 (DfT NTS, 2019). Nationally, road traffic collisions cost the UK economy more than £35 billion per year (DfT, 2019). The cyclists account for only 2% of the trip share, and 1% of the distance travelled in Great Britain. They, however, face a disproportionate share of risk and causalities. In effect, the risk currently faced by cyclists in terms of slight crashes per billion vehicle miles is 4,450, the highest amongst any road user in Great Britain and 12.5 times higher than the car users for the same traversed distance. The use of crash frequency is a recommended methodology compared with the severity in the literature (see Chang, 2006, Elvik, 2006, Holló, Eksler and Zukowska, 2010). Therefore, improving cyclists' safety to reduce cyclist fatalities is a primordial one requiring special focussed attention.

Cycling safety is an important topic, but very few studies explore the cycling risk to their exposure (Aldred *et al.*, 2018). There is a need for the capabilities to assess the safety of the experimental roadway designs and (or) operational strategies before they are built or employed in the field (Gettman *et al.*, 2008). The conventional traffic safety models are primarily developed for the assignment of the motorised modes of travel and are ill-equipped to the unique needs of the cyclist (see (Aldred, 2010; Calvey *et al.*, 2015; Lawson, 2015)). The present need of the transportation system requires cycling mode share to increase significantly. However, the major hurdle in this process is insufficient evidence to understand the relationship between cyclist safety and the identified parameters (TRL, 2011). There are very few works in the literature that undertake to model the personal attribute of the rider, variable environmental and micro-infrastructural variables affecting the safe usage of infrastructure. The current safety investigation approach may have effectively served to model the long-term safety seasonal variation with a generalised approach. However, cyclist's safety is a more complex phenomenon, which requires a more in-depth knowledge of various critical parameters.

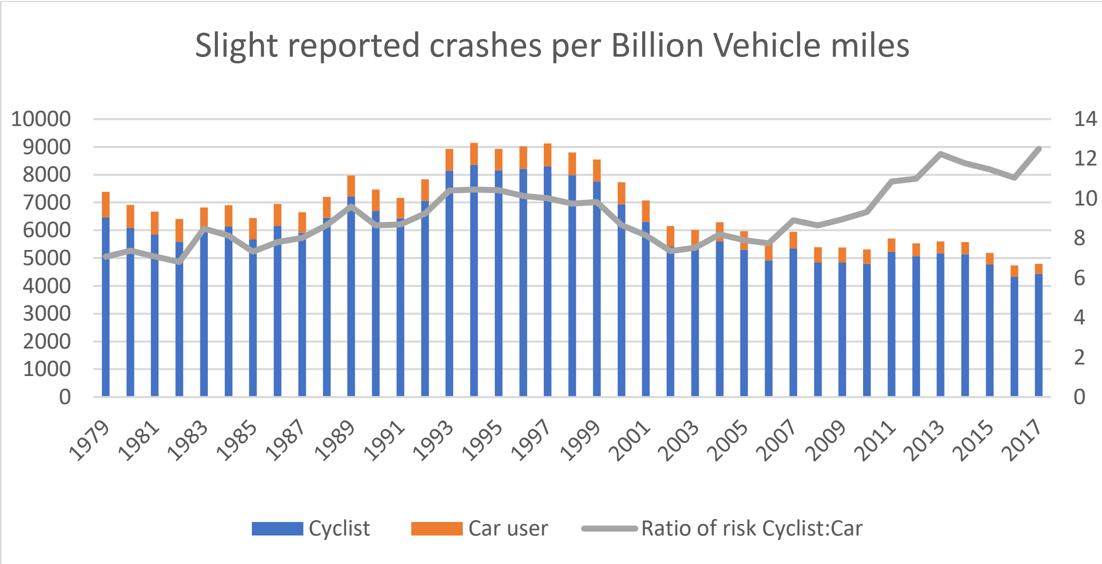


Figure 1.1. Slight reported crashes in Great Britain per billion vehicle miles, (Source: (DfT, 2018)

Through the literature review, several research gaps are identified, with the primary gap of an absence of the dynamic model for the cyclists that can predict the safety based upon dynamic input variables. Presently, there is an absence of mathematically validated understanding of how different input variables of: a) Age, b) Gender, c) Environmental, d) Micro-infrastructure variables of road types, traffic flow, road intersections, and rider manoeuvres affect the safety for a cyclist. There is a need to improve cyclist safety through a knowledge-driven modelling paradigm and an in-depth understanding of different safety performance functions.

1.3. Research questions

The following research questions are posed based upon the gap identified in the literature through the state-of-the-art review:

1. How effective is the present safety modelling, for cyclists?
2. How do the variables of a) Age, b) Gender, and c) Variable Environmental conditions, and affect a rider's safe infrastructure usage?
3. What are the safety implications of micro-infrastructure on rider safety?

1.4. Research aim

The study aims to investigate the effect of critically identified variables of rider attributes of age, gender, varied environmental condition of lighting, meteorology, and micro-infrastructure variables on the safe usage of the infrastructure for a cyclist. In this process, we aspire to develop an intelligent modelling framework and nanoscopic predictive models.

1.5. Research objectives

The following objectives are designed to achieve the set-out aim:

1. To conduct the literature review of the critical variables affecting cyclists, present mathematical models and mathematical approaches.

2. To develop a statistical model for the study area.

3. To develop an intelligent safety modelling framework combining statistical, machine learning, and mathematical approaches.

4. To develop an understanding of the interaction between infrastructure, environmental conditions, personal attributes of the rider, and safety.

5. To construct a nanoscopic safety model with the predicted outputs for: a) Personal attributes, b) Environmental conditions, and c) Infrastructure.

6. To identify and quantify the governing variables affecting the safe usage of infrastructure.

1.6. Research task

To achieve the research objectives following tasks are proposed:

1. Carry out a critical review of literature of previous studies, including cycling safety, critical safety variables, present mathematical models, and mathematical approaches to identify the research gap in the present knowledge.

2. Develop research partnerships with the requisite organisations and institutes involved with the transportation systems in the study area.

3. Determine the role of the existing cyclist crash dataset and identify the data collection method, including access from available data resources, measuring, and collecting data.

4. Assemble and critically review a wide range of statistical, machine learning, and mathematical approaches to develop a reliable and

comprehensive methodological framework. Investigate the assumptions and limitations of each method to apply the most suitable method consistent with the structure of the dataset.

5. Investigate the impact of a range of variables on cycling safety. Conduct several approaches to identify the relationship between different variables and investigate the individual and combined influence on cycling safety.

6. Develop predictive nanoscopic models for cyclist safety for each identified critical variable

7. Draw conclusions, discuss limitations, and make recommendations for designers, policymakers, and future research to improve cycling safety.

1.6. Contributions to knowledge

This work has developed an in-depth understanding of the critical identified factors of a) Age, b) Gender, c) Variable Environmental conditions, and d) Micro- Infrastructure variables, that affect the safe usage of infrastructure for a particular rider. Accurate nanoscopic predictive safety models are developed, through a case study application on Tyne and Wear. The research has exemplified the benefits of using a hybrid intelligent modelling framework. It is demonstrated that it is possible to undertake modelling for a cyclist with high accuracy and efficacy, contrary to the present available literature. It is shown that the modelling requirements and governing variables for cyclists are significantly different from the motorists, hence requiring a separate modelling framework. The work has been presented in several conferences, journal publications, and a roadmap for further research based upon the work presented in the thesis is carved out. The following is the list of publications, as the first author:

1.7. Thesis outline

The thesis begins with a state-of-the-art review of the literature in Chapter 2. The review is broadly divided into two parts, a review of the critical variables affecting cycling safety and reviewing the present infrastructure safety models and modelling approaches. The conclusion of Chapter 2 identifies the research gaps and the critical variables affecting the safety of a cyclist in its natural built environment.

Chapter 3 outlines the proposed intelligent hybrid modelling framework for cycling safety. The chapter starts with the description of the methodological framework, followed by the description of the research methods. The data sources for the study are described in detail. This is followed by a detailed description of the steps involved in modelling in further chapters.

The study area of Tyne and Wear county is described in-depth in Chapter 4. The flow conditions, variation of metrology and lighting conditions are described. The usage of infrastructure based upon the rider age and gender are also described in detail. The crash rates and variation of crashes with the infrastructure parameters are also presented.

In Chapter 5, the derivation and model development of the age variable and its safety implication is modelled. The crash rate, heat maps, deep learning neural model, variable importance, and linear regression results are described. Chapter 6 deals with modelling the gender variable. The model development is achieved through the traditional statistical model, heatmaps, deep learning neural network, critical variable modelling, and finally, through logistic regression.

Chapter 7 deals with modelling variable environmental conditions to derive their safety implications. A combination of traditional statistical models, deep learning models, causal inference models, and logistic regression models are developed. In this process, the understanding of each input variable is derived. The results and knowledge gained from Chapters 5,6 and 7 are used to develop predictive deep learning models for micro-infrastructure parameters in Chapter 8. In addition, the governing variables affecting safety are identified and quantified.

Finally, the thesis is concluded in Chapter 9, with primary findings, limitations of the study, and recommendation measures. Lastly, suggestions for further studies are provided.

Chapter 2.

State of the art review on cycling safety

The identification of the physical and environmental threats to the cyclist safety within the network allows a critical insight required for the design of new and improvement of the existing facilities (Lawson, 2015). It is essential to provide a proper cycling infrastructure that should be forgiving, safe, and provide a comfortable ride for the rider. A well-designed cycle track should accommodate cyclists of different abilities and plying at different speeds. In designing the cycling infrastructure, the designer must assume that the cyclist users are sufficiently competent and well-trained in using the bicycle. Through the literature review (Parkin, 2018) concluded that in designing for the cyclist, the foremost thing remains to provide the infrastructure fit for the purpose. As per Dutch guidelines (CROW, 2017), 'safety', 'cohesion', and 'directness' are the variables in addition to comfort and attractiveness, which are the requirements for proper cycle infrastructure. The UK Department for Transport has defined these as 'convenience', 'accessibility' and 'safety'(DfT, 2008).

The geometric characteristics of the roadway are believed to correlate with the overall crash frequency and severity (AASHTO, 2010). Noland and Oh, 2004 found that the crashes are related to the area-wide features of the infrastructure at a place (Noland and Oh, 2004). The road geometrics do not act independently of each other but in combination with other variables, such as environmental conditions and rider attributes (Imprialou, 2015). A sample of 1,402 cyclists and 73 factors were investigated to compare the influence of various factors on Canada's cyclist mode choice (Winters *et al.*, 2011), which found that primary motivators for cycling are route conditions and interaction with the motor vehicles. They concluded that to promote cycling and increase their mode share, prime importance must be given to bicycle infrastructure's location and design. Zahabi *et al.*, (2016) modelled the effect of a modal shift to cycling through infrastructure improvement. They found a positive relationship between the index of infrastructure accessibility and cycling modal share. They modelled that a 10% increase in the accessibility index will result in a 3.7% increase in ridership (Zahabi *et al.*, 2016). Abraham *et al.*, (2002) work on cyclist sensitivities found that cyclists prefer a shorter journey with this mode but are willing to cover longer distances if specific bicycle infrastructure is provided (Abraham *et al.*, 2002).

The risk cyclists confront due to changing built environments is paramount and a significant mode and route choice variable. The ease, convenience and safety can vary significantly with the physical environment that the cyclist is subjected. It is essential to provide a proper cycling infrastructure that should be both forgiving and safe. The primary motivators of cycling are the route conditions and interaction with motor vehicles. The increase in the accessibility index is directly correlated with the increase in bicycle ridership. The interaction of other road users with the cyclist is a dynamic variable affected by the infrastructure parameters, flow, cyclists' own personal attributes such as age and gender, and environmental conditions, which vary over space and time. The motorist is not significantly affected by these factors; however, these are a major contributing factor for the cyclist. It affects their daily mode and route selected for travel. The car user or the public transport users are in a closed, comparatively, safer confined environment; therefore, the modelling for cyclists needs a more in-depth knowledge of these factors. The state of art review is described in Fig 2.1, depicting the various steps performed in the study.

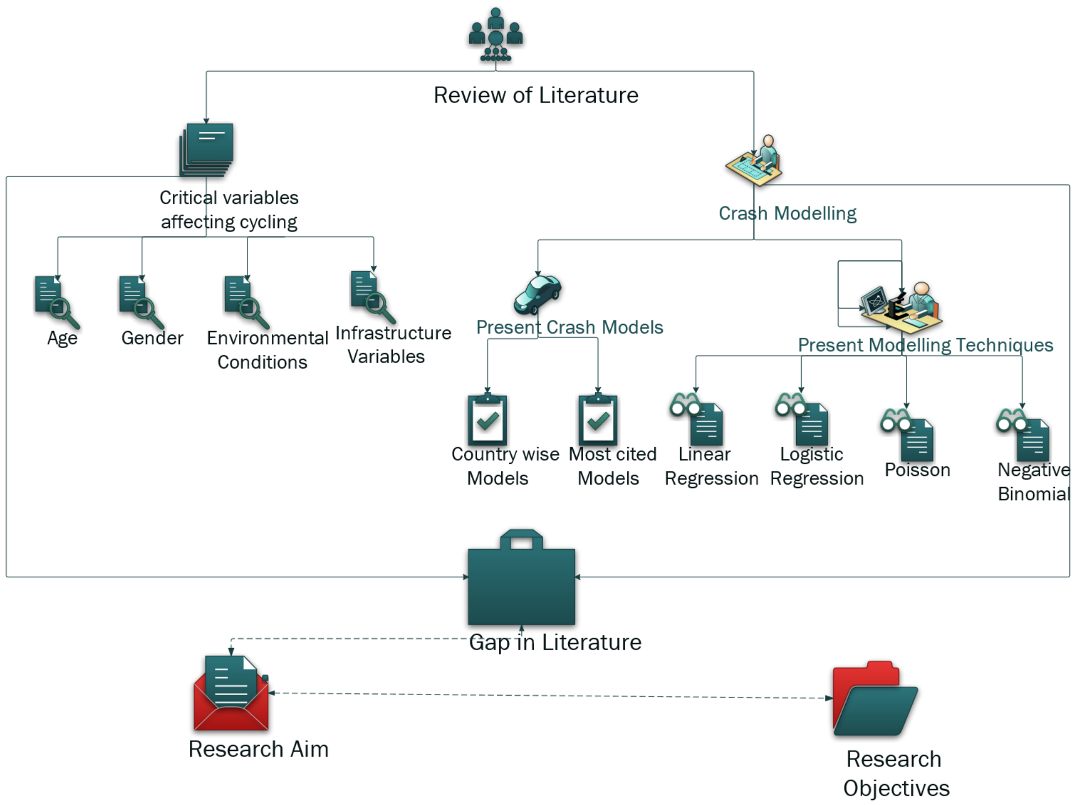


Figure 2.1. Flowchart of the review

2.1. Age

Road Traffic injuries are the topmost cause of death for the 15-29 age group (IRF, 2020). The cyclist safety is not only affected by the type of infrastructure or the type of road user it is required to interact with but also by the cyclist specific variables. The route network choice of a trip maker varies depending on its own personal characteristics as well as the behaviour of other road users (Guthrie, Davies, D and Gardner, 2001). The personal attributes include age, gender, and experience (Bill, Rowe and Ferguson, 2015). While establishing a case for American towns to learn from European countries and support cycling, Pucher and Buehler (2008) laid out future views for cycling by advocating that cycling be made safe, convenient, and feasible for people of all ages and genders (Pucher and Buehler, 2008).

In the United Kingdom and Europe, cycling tends to be dominated by younger adults (Aldred, Woodcock and Goodman, 2016). Aldred and Goodman, (2018) did a study on the near misses in London. A near miss is defined as a situation in which a crash is avoided by the driver's sudden braking and attention. A naturalistic study was performed in which the bicycles were equipped with sensors and cameras and then analysed later in the laboratory. They found that the age group that the rider belongs to directly affects their daily near misses. The number of incidents per day decreases from 2.47 (for the 20-29 age group) to 1.85 (> 60 age group) (Aldred and Goodman, 2018). These near misses are linked to the crashes, demonstrated by Hyden's pyramid. (Hydén, 1987). These near misses form the pyramid's base (Fig 2.2), with fatal crashes forming its tip (Allen and Shin, 1978; Laureshyn and Varhelyi, 2018). Another similar naturalistic study in Germany reported that cyclists also behave differently based upon their age group. The study investigated the speed and acceleration of different bicyclists types and concluded that different age groups exhibit different microscopic road traffic behaviour (Schleinitz *et al.*, 2017).

A study was carried out in Palermo city (Italy) (Potoglou *et al.*, 2018) to investigate the associations between the severity of non-fatal crashes and driver characteristics. They reported that the riders below 25 years are likely to be involved in a slight or serious crash than other riders, followed by the greater than 64 age groups; thereby concluding that young and older cyclists are more at risk than the rest of the population group. The study in England for assessing road safety (Mindell, Leslie and Wardlaw,

2012) led them to conclude that road users' risk is highest in their youth. Their risk falls with age. Similar results were also obtained in the Netherlands. For males under the age of 20, the fatality rates for drivers/car users were higher than for cycling, and the elderly population is reported at a higher risk. However, when comparing the different modes of transport, cycling has been reported safer than the younger generation's motorised mode, especially for the male population. The study in Sweden (Welander *et al.*, 1999) to understand the cyclist's injury by age and gender concluded that the females show a lower incidence than males. However, elderly women are more likely to be involved in a serious crash than younger women. The same results have been reported for males with even more difference between the young and the elderly population, and it is reported that females sustain more work trip injuries than men (Welander *et al.*, 1999).

A study was conducted on 1491 crashes on 148 roundabouts in Belgium (Daniels *et al.*, 2010), which found that the vulnerable road users are more severely affected by the difficult road infrastructure types such as a roundabout. They found that the injury severity increases with the higher age group. The crashes at night and outside the built-up area are relatively more severe. The increase in cycling traffic flow results in an increase in its safety through the established phenomenon of Safety in Number (SiN) (Jacobsen 2003); inverse relationship between the increasing number of cyclist and the likelihood of a crash. Schepers and Heinen, (2013) analysed a modal shift scenario of short tips to cycling in Netherland and modelled its effect on road safety. They concluded that the mode shift could have a substantially varied safety implication for different age groups. As the cyclist flow rate increases and a corresponding decrease in the motorists, the flow rate and composition are expected to change, affecting safety variedly for cyclists belonging to different age groups. The death rate for age group

18-64 is modelled to decrease, whereas the gain in safety in not significant for the young and elderly population (Schepers and Heinen, 2013).

One of a kind naturalistic study was performed on British roads (Walker, 2007). The author himself rode 320 km wearing everyday clothing, at a different distance from the road edge, during different times, disguising as of different sex, wearing/not wearing a helmet. He concluded that the motorists exhibit behavioural sensitivity to the bicyclist appearance. Therefore, age is widely reported in the literature as a critical road safety variable for cyclists, which acts in combination with the cyclist flow, and behavioural sensitivities of other road users to affect the safety in terms of crash frequency and severity at a particular location.

2.2. Gender

In the literature, it is widely argued that in a low cycling country (such as the UK), cycling is not evenly distributed across gender compared with the higher cycling modal share countries. The mere promotion of cycling has not created an inclusive cycling culture, and females' take-up has remained limited. To achieve a mass cycling culture, targeted infrastructure and policies towards underrepresented groups is necessary and imperative (Aldred, Woodcock and Goodman, 2016).

Women are likely to make short journeys, and their journey's spatial and temporal structure is different from men. They rarely prefer large multi-lane roads and busy junctions. Instead, they prefer selected areas of the city having narrow streets with traffic calming measures. They generally cycle at lower speeds, are more likely to make recreational rather than commuter trips, and have a stronger liking for quiet traffic streets (Beecham, 2013). The study on investigating crashes in the Czech Republic (Bíl, Bílová and Müller, 2010) reported that males account for around 69%

of the crashes, and are more likely to be involved in a fatal crash (80%). Similarly (Rodgers, 1995) in the USA found that males are at a higher risk than females (around five times more for the same distance traversed). It is common speculation that men drive less safely and more recklessly than women.

The study by (Welander *et al.*, 1999) to understand the cyclist's injury by age and gender in Sweden concluded that the females show a lower incidence than males; however, the older women are more likely to be involved in a serious crash than the younger women. The same results have been reported for males, with even more difference between the young and the elderly population. They found that females sustain more work trip injuries than men (Welander *et al.*, 1999). However, men are more reluctant to modal shift to cycling than women (Pedroso *et al.*, 2016), and it takes much more improvement in the infrastructure and environment for the women to consider cycling (Aldred, Woodcock and Goodman, 2016).

Walker, 2007, did one of a kind study on British roads in which he rode 320km wearing everyday clothing, at a different distance from the road edge, during different times, disguising as of different sex. He wore a long wig disguised as a female and surprisingly found that drivers left more horizontal clearance while interacting with him. He concluded that the motorists exhibit behavioural sensitivity to the bicyclist appearance and leave a higher margin of safety when the rider is male, rides away from the edge of the road, wears a helmet (sports attire), or when the vehicle is a bus or an HGV (Walker, 2007).

The detailed Danish study on roundabouts (Møller and Hels, 2008) through structured interviews led them to conclude that age, gender, and traffic flow conditions impact the cyclists' perceived risks. They have attributed this to the lack of traffic knowledge in specific age groups and their limited understanding of the risk as a significant contributing factor in vehicle cycle collisions. A comprehensive study was undertaken to investigate the gender difference in Italy's bicyclist crashes and fatal injury risk (Prati *et al.*, 2019). A range of crash-related data from the transport authorities, local municipalities, police agencies, automobile clubs, and the national institute of statistics was used for modelling. They found that gender is a significant variable affecting safety, with male riders being at a higher risk. They found a statistically significant effect of the variable gender for the risk faced in terms of road type, type of interacting vehicle, riskiest vehicle manoeuvres, collision type, time, day, and season of the journey. The study (Pazdan, 2020) to investigate the impact of meteorological conditions on cyclist crashes found that meteorology has a varied effect on the riskiness that infrastructure possess depending upon personal attributes of the rider (different levels of experience, age, gender, the purpose of the trip) and location of the journey in terms of countries, cities and the climate zone.

Therefore, based on the literature, we can establish that age and gender are the critical variables that affect the safe usage of the infrastructure for a rider. Neither all cyclist nor all non-cyclist is the same (Gatersleben and Appleton, 2007). Aldred, Woodcock and Goodman, 2016, recommended that to create a mass cycling culture in the country, targeted infrastructure and policies towards underrepresented groups are imperative. However, the British cycling report (Transport Research Lab report 490) argued that although gender, age, and cycling experience are critical variables affecting cyclist's safety, these variables do not influence how the cyclist rated a particular route for cyclability. The qualitative evaluation of the infrastructure is the same across age and gender (Guthrie, Davies, D and Gardner, 2001), i.e. poor infrastructure is rated poorly without bias due to these personal attributes and vice-versa.

2.3. Environmental Conditions

Meteorological conditions are a critical externality that has varying safety implications for different groups of people on various infrastructure types. The cyclist is susceptible to environmental conditions also observed in its mode and route choice. The environmental conditions can vary on a daily/hourly basis (Heinen, Maat and van Wee, 2011), affecting the selection of cycling as a mode and the safe usage of the requisite infrastructure. The literature has widely reported that extended periods of rainfall negatively affect cycling, affecting the selection of cycling as a mode of travel and its safe usage of infrastructure (Sabir *et al.*, 2009). The English and Wales mode choice model (Parkin, Wardman and Page, 2008) reported that rainfall has high negative cyclist flow elasticity, whereas lighting conditions have a positive elasticity. The variable environment conditions can result in an additional variable for the cyclist to deal/ negotiate with while interacting with the infrastructure under different traffic flow regimes, thereby acting as a significant hazard. This phenomenon can be attributed to the safety law of complexity (Elvik, 2006); which states that more the variables road user has to attend to, notable is the risk faced. The rain degrades the driving environment through various physical factors, through a possible loss of friction between the tyre and road, impaired visibility, and water spray from other vehicles (Jaroszweski and McNamara, 2014). These conditions also impact the cyclist cognitive capability (safety law of cognitive capacity), making it a potential safety hotspot. These can affect the safety variedly for a cyclist varying from one rider to another (Heinen, Maat and van Wee, 2011).

There have been some conflicting results from studies concerning the effect that the weather has on cycling safety. Some studies have shown that the probability of a crash decreases during bad weather, as drivers adjust their speed and take extra precautions (Zhang *et al.*, 2000; Theofilatos, Graham and Yannis, 2012). However, other studies have reported adverse weather conditions and poor visibility impacts unsafe driving/ riding and increases the likelihood of a crash and the severity of the injury sustained (Milton, Shankar and Mannering, 2008; Bella and Calvi, 2013). Weather is a critical mode choice variable. As the number of cyclists using the road network decreases during adverse conditions, the statistics may suggest that the number of injuries/fatalities reduces during such situations. However, each kilometre's risk per rider may have increased; therefore, the crash statistic alone may lead to improper conclusions and need to be complemented by the mode choice statistics. It is also, an inappropriate assumption that people’s travel choice does not vary over time. It is also wrong to assume that most individuals travel by the same transportation mode every day. Cyclist mode choice is expected to change even on a day-to-day basis, as they are more affected by environmental conditions, changing from day to day.

The British cycling safety report's (TRL, 2011) main finding is that for single-vehicle incidents on the highway, the cyclist's most significant infrastructure-related risk is a slippery road (weather conditions) and poor or defective road surface. Similarly, the study on university staff and students at the University of Surrey, UK (Gatersleben and Appleton, 2007) concluded that weather is a significant barrier to its uptake. Winters *et al*., (2011) did an extensive study on motivators and deterrents of cycling to compare the influence of different factors on cycling mode choice. A sample of 1,402 cyclists was studied in Canada, and 73 factors were evaluated. They concluded that cycling's primary motivators were safety, ease of cycling, weather conditions, route conditions, and interaction with the motor vehicles (Winters *et al.*, 2011).

The work on the role of attitudes towards bicycling commuting through the longitudinal survey (Heinen, Maat and van Wee, 2011) found that female cyclists are more concerned about the lighting conditions and are less likely to commute by cycle in the dark. Therefore, the absence of daylight is a significant mode and safety variable considered by females. They found that although long-distance cyclists are sometimes at the mercy of the weather, they are willing to cycle long distances and are less likely to be affected by these externalities. A part-time cyclist is more susceptible to changing their travel mode due to meteorological conditions (Heinen, Maat and van Wee, 2011). Therefore, the sample of the population using the infrastructure network during the adverse condition can be significantly different from the general population and vary in skill, experience, familiarity with the road layout, cognitive and physical capabilities. Therefore, these variables need to be handled with care, and inference should be based on due consideration to these factors.

The Italian study (Potoglou *et al.*, 2018) on crashes found that crashes were 1.6 times more likely to result in a slight or serious injury during summer, spring and autumn than those recorded in winter. The odds of morning off-peak hour accident severity are 1.6 times higher than the morning peak hour. Therefore, the environmental conditions combined with the various traffic flow regimes act as a potential safety hotspot, requiring a more in-depth understanding to uncover the underlying causation. Sabir *et al.*, 2009 work on the analysis of the meteorological impact on cycling led them to conclude that extended periods of rainfall negatively affect cycling, affecting selection of cycling as a mode of travel and safe usage of infrastructure (Sabir *et al.*, 2009).

An extensive study was conducted in Finland from 2014-16 to assess the impact of road surface conditions on road safety. It demonstrated that crash risk increases due to poor road weather conditions. They reported that the risk of adverse environmental conditions on different infrastructures is highly varied in crash frequency and impact (Malin, Norros and Innamaa, 2019). Another similar study found that extreme weather conditions substantially increase the crash rates (20% risk increase). The effect of variable environmental conditions on safety varies spatially with the month and day of the week, the journey is being undertaken (Perrels *et al.*, 2015). An analysis of the impact of road surface conditions on road safety in Iowa (USA) found pavement skid resistance significantly impacts crashes under varied environmental conditions (Alhasan *et al.*, 2018).

This combination of various factors can lead to increased crash rates due to a strain on the road user's cognitive capability (Elvik, 2006). Different road users respond differently to these road safety variables, which is also evident in their route choices (see Dublin cyclist route choice model (Lawson *et al.*, 2013)). Hyden safety pyramid represented in Fig 2.2 (Hydén, 1987) and the Swedish traffic conflict technique (Laureshyn and Varhelyi, 2018) demonstrate a pyramid-shaped relationship between the cyclist's crashes and everyday conflicts faced with other road users. These conflicts form the pyramid base, whereas crashes are the tip; both these variables are interlinked and causatives. It is well established from the literature that the cyclists' conflicts vary from user to user depending upon their personal attributes (Schleinitz *et al.*, 2017; Aldred and Goodman, 2018), traffic flow regimes (Schreck, 2017), and type of infrastructure (TRL, 2011). Overall, the literature agrees that environmental conditional affect the safe usage of the infrastructure. The increased risk reported in the literature due to varied environmental conditions of lighting and meteorological road surface conditions is summarised in Table 2.1.

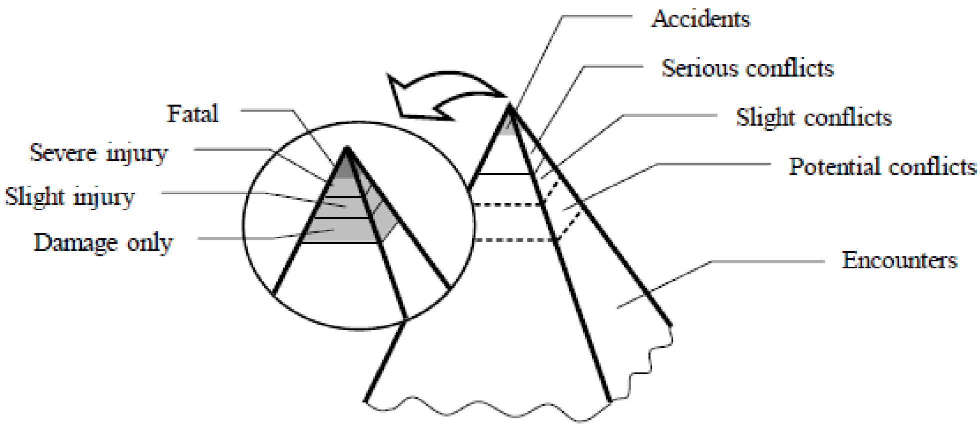


Figure 2.2. Hyden Safety pyramid from encounters to fatal crashes (Hydén, 1987)

Table 2.1. Increased risk due to varied environment conditions (lighting and meteorological road surface condition)

Study location	Period	Increased crash rate	Citation
West Virginia, USA	1970	2.2	(Campbell, 1971)
Glasgow, UK	1978-79	1.2-1.3	(Smith, 1982)
Chicago, USA	1977-79	2.0	(Changnon, 1996)
Edmonton, Canada	1983	1.3-1.9	(Andrey and Olley, 1990)
Canada	1995-1998	1.75	(Andrey *et al.*, 2003)
Melbourne, Australia	1987-2002	1.61-1.67	(Keay and Simmonds, 2005)
Iowa, USA	1965-2005	1.84	(Qiu and Nixon, 2008)
Vancouver, Canada	2003-2007	1.13-1.55	(Hambly *et al.*, 2013)
New Zealand	2012	1.35	(Jackett and Frith, 2013)
Finland	2000-2010	1.20	(Perrels *et al.*, 2015)
China	2001-2016	1.13	(Lio *et al.*, 2019)
Jordan	2020	2	(Obeidat *et al.*, 2020)

2.4. Interaction with other road users

Another critical variable is the interaction with another road user. It is essential to understand that cycling is not the same as walking, as a cycle is a vehicle capable of speed (15-30 kph), around 5-10 times higher than walking (3-4 kph) (Parkin, 2018). Therefore, the provisions for rider movement should be given separate considerations from the pedestrian requirements with different design philosophies and design elements. Various studies worldwide have shown that traffic volume has a significant and adverse effect on cyclist safety perception (Lawson, 2015).

Parkin, Wardman and Page, (2007) conducted an experiment on the passing distance that the vehicle keeps while overtaking a cyclist in the cycle lane (1.45 m wide) and non-cycle lanes. They found that the vehicles tend to keep a wider passing distance when overtaking a cyclist in a non-cycle lane (speed limit 40 mph). In comparison, a smaller passing distance when overtaking the cyclist in a cycle lane with a lower speed limit of 30 mph. They concluded that in the presence of a cycle lane, the driver tends to drive in its confined marked lane with less consideration to the cyclist needing a comfortable distance in the adjacent cycle lane. This can be attributed to several facts, such as drivers assuming that space belongs entirely to them and seeing themselves in the marked lines; they enforce their right of way (Parkin, Wardman and Page, 2007). A similar finding is reported for drivers using a shared space infrastructure, where drivers tend to be more conscious of the cyclist. Kaparias *et al.*, (2013) investigated the impacts of shared space development in the Royal Borough of Kensington and Chelsea through a behavioural observation study (video graphic) and cyclist perception survey. A before and after development study was carried out in a stretch, which was redesigned from a dual carriageway to a modern design with shared space elements. They found that development increases the number of cyclists using this facility and reduces cyclist speed. They found that cyclists dismounted varied from 17-23% (0% before the development). Even though the cyclist speed decreased, most cyclists (62%) perceived traversing the section either at the same speed or higher. They concluded that this development has led to the perceived ease in movement and perceived safety; the clarity in traversing the section was a potential threat for the cyclist (Kaparias *et al.*, 2013). Hence, it can be established that cyclists value the shared space elements, which decrease motorist speed and make them more aware of the cyclists. The shared space's infrastructure parameters are better designed for cyclist needs, which also consider their vulnerability. TfL, (2016) has recommended the degree of separation required between the cycle traffic and other movements based upon the type of network and the level of function that place offers (TfL, 2016). The motorist interaction with other road users is critical for cyclists. This interaction, combined with different infrastructure types, affects cyclist safety, ease of movement and convenience, and perceived safety.

Three critical factors that determine the comfort, convenience, and perception of safety for cyclists are (Guthrie, Davies, D and Gardner, 2001):

a. Traffic flow,
b. Traffic speed, and
c. Lane width.

The key finding of the England and Wales model (Parkin, Wardman and Page, 2008) is that the intensity of transport demand is negatively linked with commuting cycling, i.e., larger traffic volumes are linked with a lesser willingness to cycle. A study (Bill, Rowe and Ferguson, 2015) investigating cycling safety through interviews asked their volunteers to rate the identified risk in the preference for the three risk types. For the likelihood of encountering the hazard more often, they found that ‘car overtaking too closely’, ‘uneven road surfaces’ and ‘overtaking parked vehicles’ are the hazards that the cyclist believe they often encounter most regularly. The hazards ‘large vehicles overtaking too closely’, ‘vehicle emerging from junctions into the cycle paths’ and ‘car doors opening in cyclist path’ are considered by the respondents more likely to result in a crash. The respondents believed that ‘interaction with the large vehicles” can result in the most severe injuries.

The main findings of the 2011 Transport Research Laboratory report on “Infrastructure and Cycling Safety” are that wherever infrastructure does not meet cyclist requirements, they may behave in ways that could increase their risk-taking behaviour. They found that cyclist injuries to be notably higher at intersections, just as with other road users. In single-vehicle incidents on the highway, the cyclist's most significant infrastructure-related risk is the meteorological road surface condition and a poor or defective road surface. The most significant factor for multi-vehicle collisions in the infrastructure are posted speed limits, intersections, and interaction with other road users (TRL, 2011). The design speed limit is an essential variable affecting the cycling safety, as it governs the micro road geometrics such as camber, curvature, length of tangents, median width, sight distance’s, etc. (see (DMRB TD9/93, 1993; Highways England, 2016)`). The cycling mode share model (Parkin, Wardman and Page, 2008) concluded that the posted speed limit influences the cyclist's infrastructure's safe usage. Botma, (1995) in his work to determine the level of service for bicycle paths, recommended a level of service similar to a vehicle traffic flow, based upon the investigations on manoeuvres' rating regarding the hindrance (Botma, 1995). The study on the effect of the speed limit and its exceedances in the

Washington state in the U.S.A found a higher speed limit significantly increases the accident severity and chances of a fatality (Shankar, Mannering and Barfield, 1996). The cyclist is sensitive to the posted speed limit. There is a limitation to a cyclist speed and its acceleration rate, whereas a motorist does not suffer from such limitation. The motorist may start sudden acceleration (or sudden braking) with the change in the posted speed limit, negatively affecting their interaction with the cyclist. The sudden motorist acceleration can result in aggressive driving behaviour through a desire to reach the posted speed limit as soon as possible to minimise the journey time. (Chen *et al.*, 2016) analysis of risk factors affecting the severity of intersection crashes by logistic regression concluded that fatal intersection crashes likelihood increase 10.5 times within 100 km/hr speed zone than in 50 km/hr zones. (Jamson *et al.*, 2008) in their process for developing a safety vehicle index, reported that people have more tolerance towards crossing speed limit with 10% of motorist respondents not perceiving it as a safety hazard.

The various micro infrastructure characteristics complicate the cyclist's interaction variedly in combination with other dynamic variables such as the traffic flow conditions and how other road users interact with the rider (Akgün *et al.*, 2021). The safety study (Noland, 2003) on the number of lanes of different types, lane miles, and each road type's proportion (functional road types) found these variables correlate with the probability of crashes. Similarly, a study in the United Kingdom (Noland and Quddus, 2004) found that increasing the length of 'B' type roads can increase serious crashes. Amoros, Martin and Laumon, (2003) in their analysis of crashes across different counties in France, found that the crash frequency and severity are dependent upon the type of road that each county possess (Amoros, Martin and Laumon, 2003). A study was undertaken by (Stewart and McHale, 2014) to evaluate cycle lanes' effect on the horizontal distance kept by the motorists while interacting with the cyclists. They concluded that the motorist distance is not only affected by the presence of cycle lanes but also the absolute road width, presence of nearside parking and the presence of the opposing vehicle while overtaking. They reported that this variation of safe distance varies spatially and with the time of day journey is being made

There have been some conflicting results for the effect of the number of traffic lanes on safety. Some studies have attributed a reduction in safety due to an increase in the number of lanes (Persaud, 1992; L. . Chang, 2005; Kononov, Bailey and Allery, 2008), whereas others such (Ma and Kockelman, 2006) found that an increase in the number of lanes, resulted in a decrease in non-fatal crashes. The U-shaped relationship explains this discrepancy (Park, Fitzpatrick and Lord, 2010) between the number of lanes and crashes. They found that 6-lane roads are the least crash-prone compared with 4 and 8 lane roads. Similarly, a recent study to investigate the effect of geometric characteristics of the roundabout on cycling safety. Akgun *et al.*, (2018) found that the roundabout's shape or size does not affect safety. However, the probability of serious casualty increases five times for each additional lane on approach and by only 1.04 (4%) times with a higher entry path radius (Akgun *et al.*, 2018). Another reported variable affecting safety is the road manoeuvre that the vehicle may need to perform (Van Winsum, De Waard and Brookhuis, 1999; Ammoun, Nashashibi and Laurgeau, 2007). The cyclist may be required to move lanes, change the speed, or overtake the parked vehicle, negatively affecting safety. This variable, combined with the speed limit, can complicate the cyclist interaction, especially on some of the identified infrastructure hotspots.

Therefore, the traffic flow conditions, speed limit, type of roadway, number of lanes, vehicle manoeuvres, the proportion of road user types (traffic heterogeneity) and how other road users interact with the safety are critical road safety variables. The kinematic envelope of a bicycle is wider than its physical size. A buffer zone beyond the kinematic envelope is required for the cyclist while interacting with other road users (Shackel and Parkin, 2014). This buffer zone is essential for safety analysis as well as the perception of danger. This buffer zone becomes critical when a cyclist is interacting with:

a. Cyclist (Bill, Rowe and Ferguson, 2015; Lawson, 2015; Dozza, Bianchi Piccinini and Werneke, 2016),
b. Car (Guthrie, Davies, D and Gardner, 2001; Parkin, Wardman and Page, 2007; Chen *et al.*, 2016),
c. Big Vehicle (Parkin, Wardman and Page, 2007; Walker, 2007; Stewart and McHale, 2014),
d. Pedestrian (Elvik, 2009; Lawson, 2015; Werneke, Dozza and Karlsson, 2015).

The motorised modes of transport possess perceived as well as a real risk to the cycle traffic, and hence the cycle route modelling should incorporate the same for planning and design.

2.5. Infrastructure variables

An intelligent transport system should focus on transferring people from a particular origin to a given destination in the shortest possible time and aspire to enhance the rider's safety and quality. Infrastructure selection, design and planning play a pivotal role in creating a safe travel environment for road users, especially the vulnerable road user. However, its interaction with the variable road infrastructure can result in a varying level of physical and cognitive strains, impacting its safety. Identifying these physical and road environmental threats to cyclists within the network provides essential insight into cyclists' preferences and choices (Lawson, 2015). There are several studies (see (Gatersleben and Appleton, 2007; Fyhri *et al.*, 2017).), which have concluded that built environment and perception of safety are the most critical factors affecting cyclists, which vary over space and time (Heinen, Maat and van Wee, 2011).

A study was performed on the motorists on possible mode shifts to cycling (Fyhri *et al.*, 2017) through a questionnaire survey of 5,460 people in Oslo, Norway. They found that the most often cited barrier in cycling are tabulated in Table 2.2

Table 2.2. Critically identified variables affecting safety (Fyhri *et al.*, 2017)

Research question	Response percentage
Cycling infrastructure not proper	46%
Cycling feeling unsafe	40%
Bad weather	34%
Cycling as physically demanding	22%
Steep hills	18%

It is essential to understand both the actual and perceived risk to the cyclist. A well-designed cycling network should accommodate cyclists of different abilities plying at different speeds. There exists a positive relationship between the index of infrastructure accessibility and cycling modal share. The Canadian cycling commute study modelled the effect of infrastructure improvement on modal shift and found that a 10% increase in the infrastructure accessibility index can result in a 3.7% increase in ridership (Zahabi *et al.*, 2016). An individual preference study (Tilahun, Levinson and Krizek, 2007) reported that riders are willing to switch to a long journey with better facilities, such as better surface conditions, priority at junctions and bespoke infrastructure. The work on cyclist sensitivities (Abraham *et al.*, 2002) found cyclist prefers a shorter journey with this mode, but are willing to cover longer distances if specific bicycle infrastructure is provided. The investigation on modelling traffic crash occurrences in Florida (Abdel-Aty and Radwan, 2000) highlighted the importance of the road infrastructure parameters, number of lanes, median width and found them correlated with the crash probability. The overall crash frequency and severity are strongly correlated with the roadway's geometric characteristics (AASHTO, 2010). For a particular study area, crashes are related to the infrastructure's area-wide features (Noland and Oh, 2004). The road geometrics do not act independently of each other but in combination with other variables (Imprialou, 2015) to affect a particular road user's safety traversing through it.

The work on engineering condition assessment of cycling infrastructure using an instrumented cycle and user's perception of satisfaction and quality (Calvey *et al.*, 2015) concluded that the cyclist's most important factor is that the path is free from surface defects and safety that infrastructure possesses (perceived and actual). The least important factor is that the track has facilities like parking and seating (Calvey *et al.*, 2015). A cycling mode share model (Parkin, Wardman and Page, 2008) was constructed based upon the socio-economic, transport, and physical infrastructure variables in England and Wales. The key finding was that the poorly maintained pavements are a deterrent to the cyclist. They present a less attractive picture and require a more incredible amount of energy to traverse them. This is attributed to both the mental and physical strain offered by such infrastructure. They also found that the speed limit also influences the effect of infrastructure on safety.

A road safety and route choice model was prepared for Dublin city (Lawson, 2015) through questionnaire analysis. They found that cyclist has a clear order of preference, based upon the road infrastructure. They are willing to use the routes having quiet roads, perceived safer, and even alter their courses to have a continuous cycling infrastructure rather than a discontinuous one. There are three risk relationships developed for:

a) Motorist traffic flow,
b) Bicycle flow, and
c) Link capacity.

The risk increases with the motorist flow increase for the normal roadway (with no special bicycle infrastructure) and kerbside cycle path, with a more pronounced risk increase for the normal roadway. For the increase in the cyclist flow, the risk increases substantially only for the segregated bicycle facility, attributed to the rise in the cyclist-cyclist risk interaction. This interaction is expected to get complicated, as, with the increase in the flow, novice and intermediate, i.e., part-time cyclists' proportion, will increase. These lack the skills that long-term cyclist possesses. There is an expected difference in the speed, manoeuvres, and extensive braking for the people using the path as there is a skill variation. Therefore, these can result in expected encounters, negatively affecting the cyclists. However, for an increase in the link capacity, the risk decreases significantly with the increase in the capacity (i.e., design capacity/ flow) for the normal roadway and kerbside cycle lanes. The interaction of a motorist with the cyclists eases significantly as the capacity of the roadway increases. However, the segregated cycle lane and the shared bus lane are not affected by motorists interacting as they are independent infrastructure types.

Transport research Lab conducted experiments with 51 cyclists riding an instrumented bicycle on a set route encountering different road infrastructure types, with volunteers asked to make a personal assessment of the 11 links in the route based upon the road and traffic conditions on a scale of 1 to 10. They observed that rider's overall valuation of the perceived safety is quite similar. Particular infrastructure features negatively affect the ease of movement and comfort, which affect the perceived risk, manner of interaction and rating of the infrastructure (Guthrie, Davies, D and Gardner, 2001). A similar bicycle route choice study (Sener, Eluru and Bhat, 2009) concluded that the cyclist route choice depends on the route's attributes and the cyclist demographics. Although travel time is a crucial attribute for cyclist mode choice, traffic volume, on-street parking characteristics, the number of stop signs, speed limit, continuity of cyclist route, cross streets, red lights, and road infrastructure terrain are also critically considered parameters.

The cross-country work on cycling safety and geometric roundabout parameters in Belgium and UK (Akgün *et al.*, 2021) led them to conclude that as design parameters and standards vary from country to country, a corresponding change in safety and blind-spot mitigation occurs. This reinforces this variable's dynamic nature, which needs to consider while performing safety evaluation and network design. The infrastructure design and network planning need to be conducted through an in-depth investigation and knowledge-driven approach based on local practices and knowledge. Cycling safety is a complex, dynamic multifactored variable. A single solution may not suffice, and it may require optimising through several possible solutions. A particular best network at a particular location may not be the most appropriate at other sites, e.g., an argument put forward to promote cycling is to have a fully segregated infrastructure. However, such a single focussed system will not achieve a sustainable and intelligent transportation system. A segregated cycle lane may appear to present a degree of visible separation from the primary motorised traffic. Still, they may, in some cases, affect the free movement of a cyclist by encountering them to the extreme left-hand side of the road. This can prove hazardous, especially at intersections where HGV's are turning left, placing the cyclist outside drivers central vision is or, in some cases, in their blind spot. (Stewart and McHale, 2014). Also, such an infrastructure type may significantly increase travel time, thereby discouraging the mode's use. A perceived cycling risks model (Parkin, Wardman and Page, 2007) was developed through video clips of routes and junctions, shown to 144 commuters and then evaluated. They found that bicycling facilities around the motor trafficked routes and at junctions have little effect on the perceived risk. They suggested that the provision of facilities at the junctions can even have a counter-intuitive impact on the users. It may indicate to the potential cyclist that the intersection is riskier than otherwise perceived. The study challenged the assumption that bicycle lanes will encourage bicycle use. They argued that the two-way easy traffic flow and the decrease of on-road parked vehicle also impact the perceived risks, similar to the segregated lanes. They recommended a coherent network of well-signed routes which are comfortable, attractive, and direct. Similar results were also reported by the British road safety study (TRL, 2011) that there is little evidence to suggest that the bespoke cycle lanes increase the safety

Therefore, we can conclude that different infrastructure types present a varying level of risk to cyclists. The infrastructure does not act independently but combined with the flow conditions to present a varying risk level to the same rider. There have been some conflicting results reported in the literature regarding the type of infrastructure and the number of lanes, which needs to be addressed to help to design and plan. The main limitation of these studies is that they only report the variables without mathematically modelling or validating them. Through mathematical modelling only, requisite confidence for policy implications and knowledge-driven recommendation measures can be achieved

2.6. Summary

The infrastructure's safe usage is affected by a combination of variables, including traffic flow regimes, environmental conditions, and the rider's personal attributes. The motorised modes of transport pose perceived as well as a real risk to the rider. The variable environmental conditions of lighting and meteorology vary significantly, affecting the safety variedly (Parkin, Wardman and Page, 2008; Heinen, Maat and van Wee, 2011). The risk of adverse environmental conditions on different infrastructures is highly varied in crash frequency and impact. The variable environmental conditions have a varied effect on the riskiness that infrastructure possess depending upon the rider's personal attributes (different levels of experience, age, gender, purpose of the trip) and location of the journey in terms of countries, cities and the climate zone. The effect of variable environmental conditions on safety varies spatially with the month and day of the week journey is being undertaken. Different infrastructure types present a varying level of risk to cyclists. The road type, including its speed limit, number of lanes, and the corresponding vehicle manoeuvre that the rider may perform, are safety variables critical to a cyclist. The infrastructure does not act independently but combined with the flow conditions to present a varying risk level to the same rider. The rider's personal attribute; age, gender, and time of the day journey is undertaken (Bill, Rowe and Ferguson, 2015) are also independent critical safety variables. It is widely reported in the literature that the journey types and infrastructure route choice correlate with the gender of the cyclist (Gatersleben and Appleton, 2007) (Beecham, 2013). However, this is a spurious relation with the lurking variable (confounder) being safety. These personal attributes of a rider in combination with infrastructure parameters pose a varying level of risk to the rider (see Dublin cycling model (Lawson *et al.*, 2013), London cyclist near miss study (Aldred and Goodman, 2018)), to which riders respond differently evident in their journey choices. Therefore, based on the literature review, we can establish that the following variables (Table 2.3.) critically affect the infrastructure's safe usage.

Table 2.3. Critical variables affecting safety

Variable	Citation
Age	Mindell, Leslie and Wardlaw, 2012; Schleinitz *et al.*, 2017; Aldred and Goodman, 2018.
Gender	Gatersleben and Appleton, 2007; Aldred, Woodcock and Goodman, 2016; Pedroso *et al.*, 2016.
Environment conditions	Heinen, Maat and Van Wee, 2011; Perrels *et al.*, 2015; Potoglou *et al.*, 2018.
Types of Roads	Amoros, Martin and Laumon, 2003; Noland and Quddus, 2004; Lawson, 2015.
Traffic flow	Parkin, Wardman and Page, 2007; Walker, 2007; Stewart and McHale, 2014.
Road Junctions	Beecham, 2013; Imprialou, 2015; Chen *et al.*, 2016; Akgun *et al.*, 2018.
Vehicle Maneuvers	Van Winsum, De Waard and Brookhuis, 1999; Ammoun, Nashashibi and Laurgeau, 2007; Bill, Rowe and Ferguson, 2015.

All these variables, both individually and in combination, have a negative impact on cycling safety. The Swiss cheese model of accident causation best explains the interaction of these variables (cumulative act effect) (Larouzee and Le Coze, 2020).

The British psychologist James Reason (Manchester University) first proposed the Swiss cheese model to describe the hazards of failure from the complex system (ergonomics) while interacting with the human, technological and natural components. In this model, the variables (defences against failures) are modelled as a series of barriers, represented by the cheese slices (Fig 2.3). These cheese slices are Swiss cheese with holes (eyes), representing the variables' weakness varying in size and position across the slices. The system results in a failure through the trajectory of accident opportunity, i.e., when the holes in the slices momentarily align so that the hazard passes through all the holes in all the slices, leading to a failure.

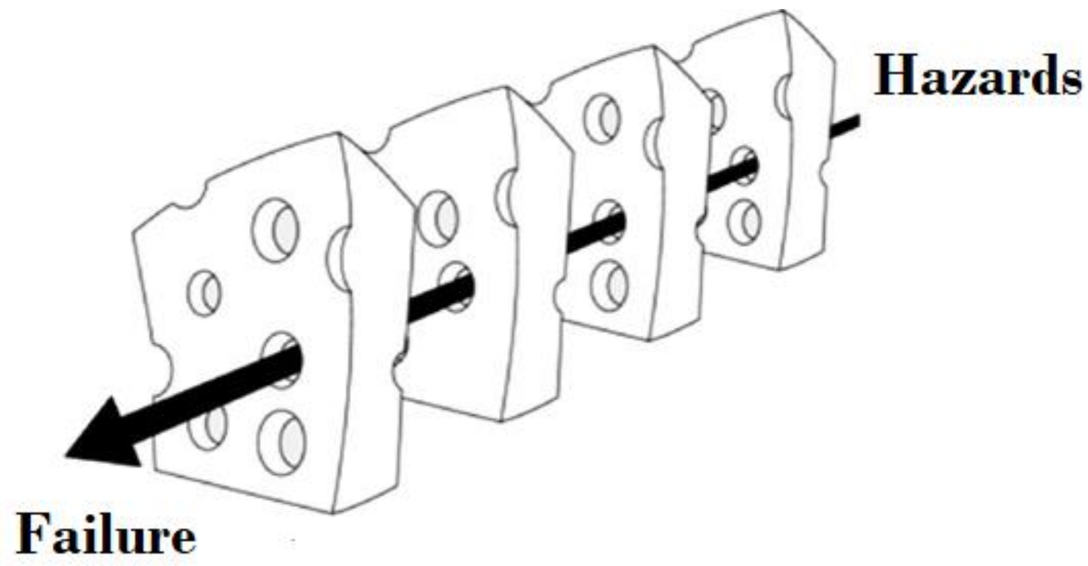


Figure 2.3. Swiss cheese models (Larouzée, 2017)

The two cheese models for road safety analysis based upon the review of literature are presented in Fig 2.4, and Fig 2.5, for males and females respectively. As a result of applying the Swiss cheese model to cyclists, the infrastructure becomes risky when passing through the cheese holes (variables) of:

a) Age,

b) Gender,

c) Environmental conditions,

d) Traffic flow conditions,

e) Interaction with other road users (traffic flow), and

f) Infrastructure variables (road type, junction type, and vehicle manoeuvre).

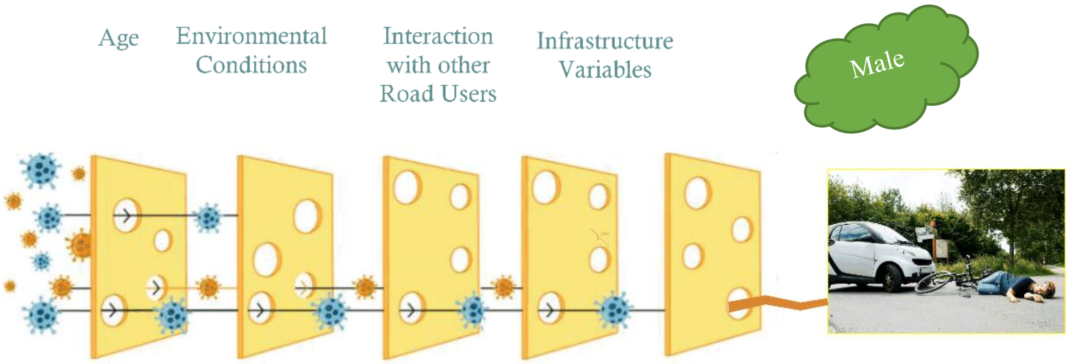


Figure 2.4. Swiss cheese model for cycling safety for males

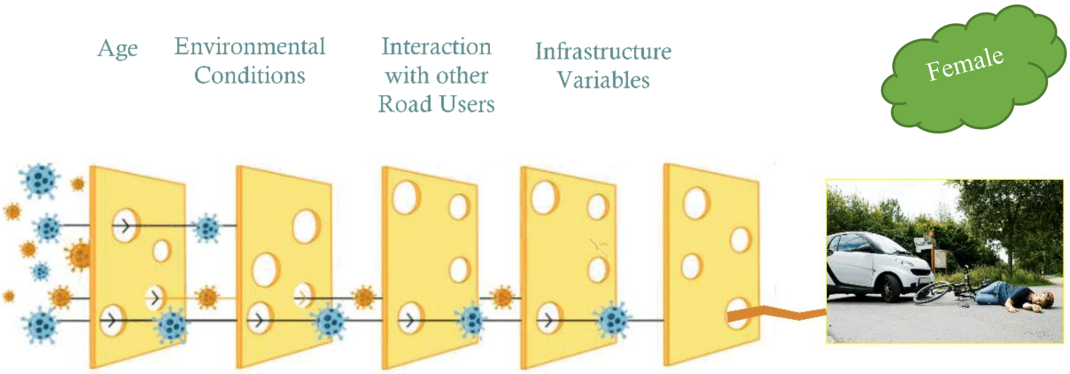


Figure 2.5. Swiss cheese model for cycling safety for females

2.7. Safety models

After establishing the importance of various variables affecting cycling safety, it is imperative to understand the modelling procedure. The infrastructure safety analysis is performed by developing safety models whose accuracy and efficiency directly impact road safety investigations, remedial measures, planning, and design. A model is a simplified representation of the previously acquired knowledge to help develop the understanding of various phenomena, the interaction of variables, causation, predicting future variation and behaviour, and ensuring that the policy is based upon scientific knowledge. A model is essentially a tool that aids in the efficient use of resources, the prediction of failures, and the development of countermeasures. The models are generally divided into four categories:

a) Physical,
b) Mathematical,
c) Descriptive, and
d) Visual.

The utility of model is dependent upon the context and application. In this section, the crash theory is first defined, followed by the crash prediction models and mathematical approaches used to model them.

A theory does not exist a theory to indicate how the accident frequency increases as the flow characteristics change or how crashes are affected by the infrastructure parameters (Gettman *et al.*, 2008; Hauer, 2015). Statistical Road Safety Modelling (SRSM) is the fitting of a statistical model to the data. The whole process of SRSM is that of the curve fitting, in which the modeller chooses the function going to fit the data. The modeller does not have any guidance form the theory, not even the dimension analysis when selecting the function (Hauer, 2014). As a result, no physical models exist for road safety. SRSM results in an equation with the estimate of the expected accident frequency (safety) on the left-hand side and a function of traits on the right-hand side. It has two primary uses; to estimate the predicted accident frequency (safety) of a particular infrastructure element based upon the specific characteristics and estimate the change in the expected accident frequency (safety) caused by the change in any trait (Hauer, 1997, 2015). There are two kinds of clues that depict its ‘unsafety’ to assess an entity's risk. The first one being the traits such as the flow conditions, infrastructure parameters, and the second one being the historical crash data. The entity can be a segment of a road or an infrastructure, or a combination of both (Hauer, 2014). The safety models have become the essential scientific tools in quantitative safety management, thereby forming the foundation of the AASHTO’s Highway Safety Manual (HSM) (AASHTO, 2010).

The safety models consist of safety performance functions (SPF), the mathematical equations based upon the specifically identified traits. These SPF’s are used for:

a) Network screening,
b) Countermeasure comparisons, and
c) Project evaluation.

These SPF’s are developed using data from specific locations for a specified time and generally represent the average condition at that site (AASHTO, 2010). One way of investigating infrastructure safety is to use the historic crash numbers and compare them with the average values that may be either location-specific or distance-based. However, the recommended methodology for investigating safety is to develop predictive models. These models should estimate infrastructure safety by using the infrastructure characteristics and empirical knowledge on how the crashes are affected by the infrastructure characteristics (Peltola, 2000; Greibe, 2003).

2.7.1. Present Mathematical Models

It is essential to first investigate the theory behind the crash prediction models (CPM) before reviewing the CPM themselves. The theory behind the present crash models is that the human element (road user error) is the primary cause of a crash (Sabey and

Taylor, 1980; Carsten *et al.*, 1989), Fig 2.6. An extensive study was undertaken in the United Kingdom by Transport Research Lab (TRL, 2002), regarding the crash causation, and the contribution of three primary factors of a) Human element, b) Faulty road infrastructure, and c) Failure of vehicle components was evaluated and modelled. It was concluded that if the human element is completely taken out of the picture, around 95% of crashes won't occur. Crashes are complex events, often resulting from multiple contributing factors. Human behaviour, the roadway environment and vehicle failures are factors found to contribute to around 94%, 34% and 12% of crashes, respectively. The findings and the contribution of each factor, (individually and combined), are explained in Fig 2.7. The present crash models are based upon these theories, resulting in the prediction models that are essentially probabilistic functions of human error.

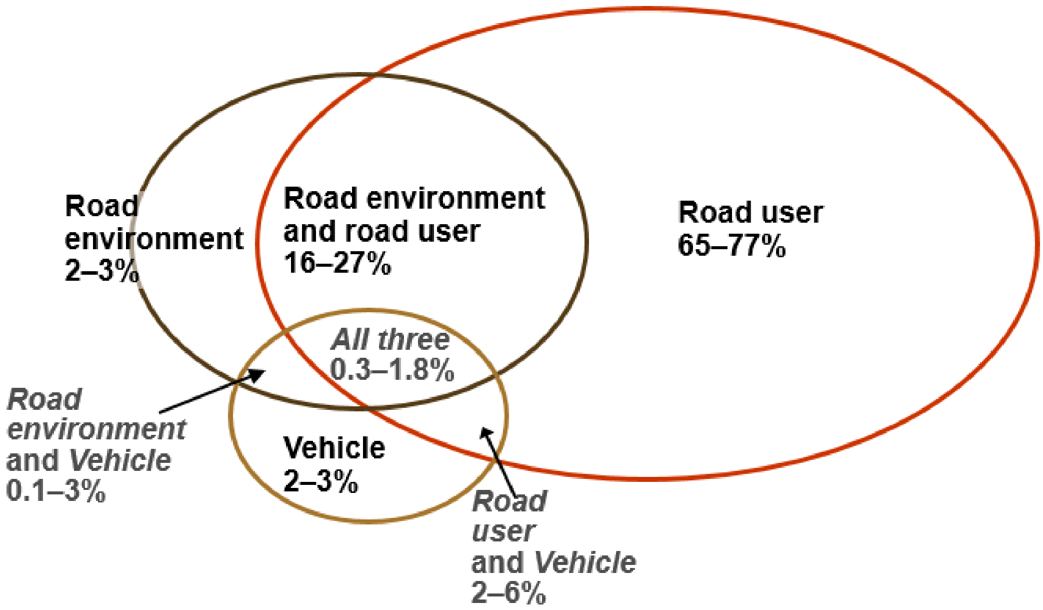


Figure 2.6. Venn diagram showing the cause of the accident (Sabey and Taylor, 1980; Carsten et al., 1989)

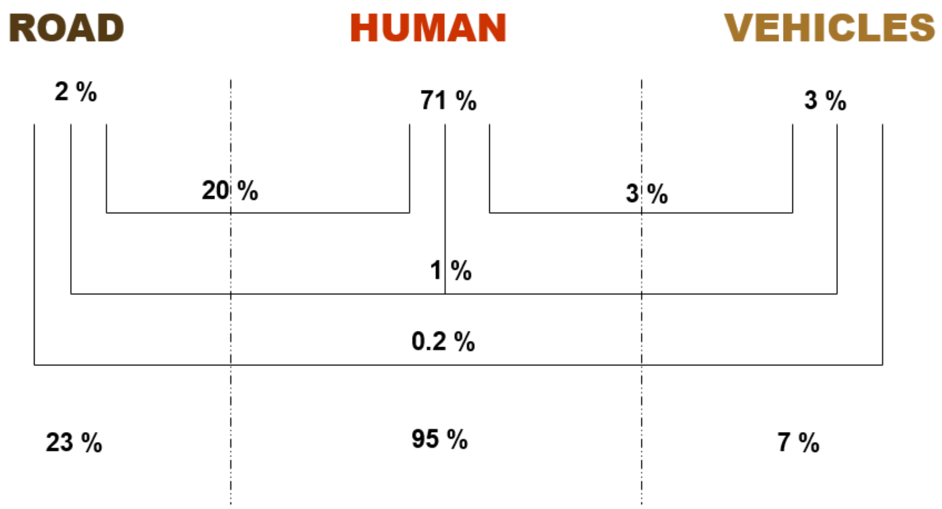


Figure 2.7. TRL Crash causation factor in the UK (Barrell, 2017)

In each country, the policy is driven by the respective highway agencies. As a result, a review of the primary highway agencies' crash models is conducted, and the key variables modelled in these models are identified.

a. United Kingdom: Transportation Research Lab (Connors *et al.*, 2013): The expected number of crashes μ_i at the site i over a time period of T are given by

$$\mu_i = a_1 T Q^{a_2} L e^{\frac{a_3}{L}} \tag{2.1}$$

where L is the link length in kilometres, Q is the flow (two-way AADT in thousands), $a_1, a_2,$ and a_3 are the constants, obtained after validation.

b. USA /Canada Model: (AASHTO, 2010)

$$\ln P_c = \alpha_1 + \ln A^{\alpha_2} L \tag{2.2}$$

For Intersections

$$\ln P_c = \alpha_1 + \ln {A_m}^{\alpha_2} {A_n}^{\alpha_3} \tag{2.3}$$

where P_c is the predicted crashes, A is the annual average daily traffic, A_m is the annual average daily traffic on major road, A_n is the annual average daily traffic on minor road, L is the segment length , α_1, and α_2 are the constants obtained after model validation.

c. Danish Model (Greibe, 2003)

$$E(u) = \alpha N^P e^{\sum \beta_j x_{ij}} \tag{2.4}$$

where $E(\mu)$ is the expected number of accidents (accidents per year per km), N the motor vehicle traffic flow (AADT), x variables describing road geometry or environment of the road $a, p, and \ \beta_j$ are estimated parameters after validation.

d. Swedish Model (Jonsson, 2005)

The following variables are modelled in the Swedish safety model:

1. Road Users; MF : Motorised vehicles, C : Cyclist and mopeds, G : Pedestrians
2. Accident rate and severity; Ok: Accident rate per million axle pair km, SF: Number of injured and killed per accident, AF: Number of seriously injured and killed per accident, EF: Number of properties only accidents per total number of accidents.
3. Environment; Y: Urban area, outer part, M: Urban area, between outer and central part, C: Urban area, central part, L: Rural area.
4. Road Function; GIF: Thoroughfare, entrance route, by-pass, $Tang$: Tangential street, $City$: City centre streets.

e. TRAVA: Finnish Model (Peltola, 2009)

$$E = 0.156\, M \prod_{i=1}^{6} A_i \tag{2.5}$$

where, E is the expected number of injury accidents per year, M is the motor vehicle mileage, expressed as millions of kilometres/years, A is the constant signifying the infrastructure parameters.

$A_1 = 1$, if speed limit $= 50\ kmph$, $A_1 = 0.619$ if speed limit $= 60\ or\ 70\ kmph$, $A_1 = 0.662$ for $80\ kmph$ speed limit, $A_1 = 0.604$ for $100\ kmph$ speed limit

$$A_2 = e^{(0.00091\, L_i)} \tag{2.6}$$

$$A_3 = e^{(-0.005882\, S_{300})} \tag{2.7}$$

$$A_4 = e^{(0.0279\, H)} \tag{2.8}$$

$$A_5 = e^{(0.0748\, R_j)} \tag{2.9}$$

where L_i is the %age of lighted road length, S_{300} is the %age of road length having greater than 300 meter sight distances, H is the %age of heavy vehicles, R_j is the number of busy junctions per road kilometre.

$A_6 = 1.127$ if the road is paved with width of pavement less than 6.9 m, $A_6 = 1.046$ if the road is paved with width of pavement is greater or equal to 6.9 m, $A_6 = 1$for the unpaved (gravel) road.

A crash modification factor is a ratio of calculated to the observed crashes, also known as collision modification factors, which is applied to different sections after calculating it for a particular location (Peltola, Rajamäki and Luoma, 2012)

f. DRAG Model (Demand for Road use, Accidents and their Gravity) (Gaudry and Lasarre, 2000).

In DRAG models, the exposure is described as total mileage for cars and calculated from the total fuel consumptions. The variables used for expressing the risks are alcohol, medical consumptions, average speeds in the region, traffic flow and other variables on an aggregate level such as that on a city or a district level. The result from such types of models is like the effect of a seat belt or the change in the level of prescribed alcoholic consumption or such things. (Gaudry and Lasarre, 2000).

The other commonly cited models in literature include (Kutner et al., 2005) model for four-arm intersection, which take input variables of AADT, speed limit, and the micro infrastructure parameters. Salifu, (2004) in Ghana constructed a log-linear model based on traffic flow/control and geometric design feature (Salifu, 2004). Similar variable classifications were used by (Bauer and Harwood, 2000)'s negative binomial model in California. Kumara and Chin, (2003) performed a road safety investigation on a T intersection in Singapore for nine years from 1992-2000. They used the zero-inflated negative binomial model for investigating these similar variables (Kumara and Chin, 2003). The quasi exposed multiple logistic regression model by (Yan, Radwan and Abdel-Aty, 2005) modelled 16 variables, including the age in the multi-vehicle rear-end crashes. They found that the driver age to be significantly associated with safety at a 95% confidence interval. However, they were not able to validate their results or evaluate the accuracy of the found relationship. From the review of the literature, the main variables modelled in the road safety models are Annual Average Daily Traffic (AADT), road geometry, micro-infrastructure variables, infrastructure management, and crash management. The most cited safety models are presented in Table 2.4.

Table 2.4. Main road safety models and variables modelled

Citation	Study location	Variable modelled
(Bauer and Harwood, 2000)	California, USA	Traffic flow, traffic control, and geometric feature
(Kumara and Chin, 2003	T intersection in Singapore	Traffic flow/control, and the geometric details of the infrastructure
(Greibe, 2003)	Denmark	AADT, and road geometry
(Salifu, 2004)	Ghana	Traffic flow/control and geometric design feature
(Jonsson, 2005)	Finland (TRAVA)	Speed limit, number of intersections, lighted, paved road, sight distance, congestion, number of vehicles and percentage of heavy vehicles
(Kutner *et al.*, 2005)	Four arm stop controlled/ signalized intersection	Speed limit and the micro infrastructure parameters
(Hirasawa, Asano and Saito, 2005)	Japan	Road classification, design speed, cross sectional infrastructure elements, traffic flow, number and type of intersections, layout, road surface conditions, and the type of road user involved
(Dandona, 2006)	India	Type of crashes, legislation, law enforcement, emergency crashes
(Whitefield, 2009)	Jakarta, Indonesia	Knowledge of hazards, management of network, safety control, management, and leadership, workplace audits, safety attitude survey
(AASHTO, 2010)**.**	USA/Canada	Annual Average Daily Traffic (AADT) on minor and major road

(Holló, Eksler and Zukowska, 2010)	Central Europe	Plan, and management of road network, entry and exit of vehicles, recovery, and rehabilitation of the victim
(Gaal, Verstappen and Wensing, 2011)	Multi-country web-based questionnaire model	Facilities, patient safety management, education
(Newnam and Watson, 2011)	Review of literature and a theoretical, conceptual framework	Pre-crash (journey details, infrastructure parameters), At scene management, post-crash care
(Connors *et al.*, 2013)	Great Britain	AADT and the length of the investigated infrastructure

These crash prediction models are primarily based upon the flow, annual average daily traffic on major and minor roads, type of vehicles plying, post-crash and infrastructure management, and the micro infrastructure variables. The output is in the form of probabilities based upon the average distance and severity of the crash, either in fatalities or crashes per year. For cyclists, mode selection and safety are highly correlated (Guthrie, Davies, D and Gardner, 2001; Parkin, Wardman and Page, 2008; Laureshyn *et al.*, 2017). None of the models can either evaluate the cyclist safety at a location or quantify how the change in the infrastructure will affect their safety. The critical exposure variables found in the cyclist literature (Table 2.3.) are not included in these models. The present crash models are unable to quantify various research in cycling safety, including the effect of age, gender, and specific riding manoeuvres required to negotiate an infrastructure. Numerous works in the literature have argued that these conventional traffic models have been developed for the assignment of motorised modes of travel only and are not equipped to the cyclist's special needs (see (Aldred, 2010; Calvey *et al.*, 2015)).

In one example, (Lawson, 2015) applied the minimum travel path algorithm for the cyclist, the standard modelling technique for motorised route choice (Ortuzar and Willumsen, 2001), by selecting a study network for investigation in Dublin. Two paths were chosen on a major cycle route, with both the paths starting and ending at the same point, depicted in Fig 2.8, a) Fitzwilliam street, and b) Grand Canal cycle path. She applied the minimum travel path algorithm as recommended by the local highway agency National Transport Authority. The Department for Transport in the UK (DfT TAG, 2017), and all the other major highway agencies, including AASHTO recommend the same. The minimum travel path algorithm results resulted in most of the cyclist assignment to Fitzwilliam street. However, in practicality, she found a high traffic flow on the grand canal road, and very few, if anyone, used the latter road (Fig 9). They found that the safety attributes of both routes were significantly different. The grand canal route provided a significantly higher perceived safety and infrastructure there was much more suited for the cyclists than the Fitzwilliam street. This led them to conclude that cyclist route choice is significantly dependent upon safety. This variable is not considered by the 'Minimum travel path' algorithm; therefore, inaccurate results were obtained, contrary to the cyclists' selection.

Additionally, none of these models can be applied to a network in the planning stage as the new facility, or even the redeveloped facility will not have any crash record or the flow plying on them before being operated. To achieve a holistic, sustainable transportation system, (Gettman et al., 2008) stressed the need to model cycling safety for the projects in the planning stage. This will ensure that safety is considered from the initial planning stage and result in a pro-active approach to road safety. At present, a reactive approach is applied in which road safety analysis is usually performed when the requisite number of fatal crashes have occurred.

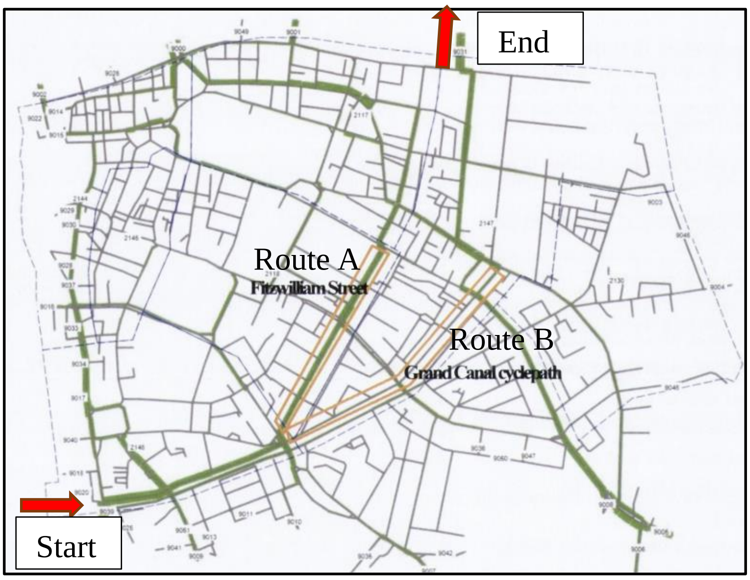


Figure 2.8. Study Area used to apply minimum travel path algorithm in Dublin, (Lawson, 2015)

a) b)

Figure 2.9. Difference in the traffic flow between a) Grand canal road, and b) Fitzwilliam street

2.7.2. Various Mathematical approaches applied for crash safety models

To model crashes, a range of mathematical methodologies have been explored over the years. A comprehensive methodological review of the approaches for investigating and modelling crashes is presented by (Mannering and Bhat, 2014). The first application of the crash prediction model started in the 1980s (Maher, M and Summersgill, 1996). Firstly, generalised linear modelling was used for modelling crashes. Then various studies proposed a generalised linear model for collisions (Lovegrove and Sayed, 2006; Popescu, 2016; Kasm *et al.*, 2019) with the assumption of a non-normal error structure, usually either a Poisson or a negative binomial error structure. This overcomes the limitations associated with the linear regression models and producing a better fit to the observed collision data (Lovegrove and Sayed, 2006). As the crashes are discrete variables, therefore Poisson regression was explored by the researchers. However, these have the limitation that they cannot handle overdispersion (i.e., the variance exceeding the mean). This motivated using negative binomial or Poisson gamma models, assuming that the Poisson parameters follow a gamma distribution (Ambros *et al.*, 2018). The following main mathematical approaches have been applied in the crash modelling:

2.7.2.1.Multiple Logistic Regression

As the name suggests, multiple refers to many explanatory variables. Multiple logistic regression models describe the association between the binary outcome and a set of explanatory variables which are being investigated. The primary advantage of this method is that it can be interpreted using the odds ratios (Agresti, 2002). Multiple logistic regression techniques have been applied to several crash studies such as (Al-Ghamdi, 2002; Wong, Sze and Li, 2007; Tsui *et al.*, 2009)). However, this method's main limitation is the inability to model the scenarios in which the crash outcomes are continuous (Nambussi, Brijs and Hermans, 2008).

2.7.2.2. Multiple Linear Regression Models

The multiple linear regression method investigates the relationship between a continuous outcome and a set of explanatory variables. Multiple regression modelling is not a proper method to be applied to the crash investigations as it is based upon the assumption that the data follows a normal distribution. A normal distribution covers all numbers on a real interval, not an appropriate assumption for a crash dataset. Although this statistical method has been widely used in crash investigation, this limitation makes it inappropriate for modelling road crashes (Chin and Quddus, 2003). This approach can result in outputs, which are non-integers as well as negative. These two conditions are inconsistent with the continuous crash data modelling. Another limitation of this approach is that there may be data points having zero value. This makes the transformation of the positively skewed distribution to a normal distribution difficult (Abdulhafedh, 2017).

2.7.2.3.Poisson Models

As the crashes are discrete and random, Poisson distribution appears to be a more appropriate method. The Poisson distribution is appropriate when discrete response variables are counted as possible outcomes (Nambussi, Brijs and Hermans, 2008). The Poisson distribution overcomes skew, discrete distribution, and restriction on the non-negative values that the distribution can assume (Glenberg, 1996). Therefore, Poisson distribution is considered a better approach for modelling crashes. It is different from the ordinary linear regression models in two ways. Firstly, it assumes that error components are not normally distributed. Instead, they follow the Poisson distribution. Secondly, the response variable is modelled as the natural log of the response variable as a linear function of the coefficient (Abdulhafedh, 2017). The primary assumption in using Poisson distribution is that the mean and variance are both equal (Glenberg, 1996).

However, the crash dataset is mostly prone to overdispersion, i.e., the variance is greater than the mean. The results derived in such cases will be biased. Hence, the test statistics derived in such circumstances will be incorrect and will result in an inaccurate estimation of the crash's likelihood (Chin and Quddus, 2003).

2.7.2.4.Negative Binomial Models

To overcome overdispersion, negative binomial models are used to relax the mean's condition and the variance being equal. This, therefore, gives the capability to take into account overdispersion in modelling (Lord and Mannering, 2010), done by introducing an overdispersion parameter in the model. The negative binomial method uses the Gamma probability distribution and is also called the Poisson-Gamma distribution model (Abdulhafedh, 2017). The negative binomial regression models have more desirable properties than the Poisson distribution for modelling road safety (Chin and Quddus, 2003; Nambussi, Brijs and Hermans, 2008).

This main limitation of this method is its inability to consider the under dispersion, i.e., mean being greater than the variance. There can be locations/junctions having zero crashes. If zero number of crashes are recorded at a location, such cases represent a relatively safer site. However, if such places are more common, there can be an overrepresentation of these zero sites in the models, causing under dispersion.

However, there are other proposed, less used mathematical techniques such as Poisson–Log normal Regression Method, Zero-inflated Poisson, and Empirical Bayes Method (Deublein *et al.*, 2013; Lawson *et al.*, 2013; Akgun *et al.*, 2018), but all of them suffer from similar limitations. All these methods assume the independent residuals across the number of crashes. The correlation within the clusters is a commonly observed phenomenon in the crashes, thereby violating the residues' assumption. As the crashes' variables are likely to have location-specific effects, these non-hierarchical models are not a proper methodology to apply to the crash database.

If the existent correlation within the clusters is taken into account, i.e. without considering the hierarchy, the resultant output is the biased parameter estimates and the biased standard errors (Kim *et al.*, 2007).

The primary benefits and limitations of these primarily used mathematical techniques are presented in Table 2.5**.** Gaber and Wahaballa, (2017) found from the review of literature that although in the literature, there have been several crash prediction models constructed using Poisson regression models, negative binomial regression and multinomial model using generalised linear regression methodology. However, these are insufficient to model the relationships between the crashes and the contributing variables. This is attributed to the non-linear and complicated relationship, which these simple mathematical techniques cannot handle. This led them to conclude that road traffic crashes cannot be modelled using these traditional methods (Gaber and Wahaballa, 2017). Another limitation of these conventional methods is that the resultant models assume a function based on previously observed crashes. None of the traditional models can be applied for any change in the infrastructure or the traffic flow variation or a project in the planning stage (Kim *et al.*, 2007). As the facility has not yet been constructed, there are no crash records avai-

Table 2.5. Advantages and disadvantages of the primary mathematical techniques used for crash modelling

Modelling technique	Advantages	Disadvantages
Multiple Logistic regression	Can evaluate the effect of one variable while controlling other variables, interpretation can be performed using the odds ratios	inability to model scenarios in which the crash outcomes are continuous

Multiple Linear Regression	Model the scenarios where crashes are continuous	Assumes normal distribution, can result in non-integer outputs, difficult to transform positively skewed distribution to a normal distribution. Unable to handle random, discrete events, and may even result in a negative value.
Poisson Model	Better able to handle discrete and random events. Overcomes skew, discrete distribution, and restriction on the non-negative values that the distribution can assume	Based upon the assumption of mean and variance being equal, therefore, cannot handle over or under dispersion
Negative Binomial model (Poisson-Gamma)	Overcomes overdispersion, not based upon the assumption of mean and variance being equal. Able to describe random, discrete, and sporadic crash events	Cannot handle under dispersion and small sample size.

-lable for such facilities (Gettman *et al.*, 2008). This results in a reactive approach in which any change in the infrastructure or a recommendation measure can only be undertaken after several crashes have occurred of a certain severity. This is unethical and contrary to the 2030 zero road traffic fatality vision. This limitation has led to the road safety variable's omission in modelling/designing a new infrastructure scheme.

Hence, to improve the modelling capabilities, new techniques are being investigated to overcome the limitations of these traditional methods. These include Random effect models (see (Anastasopoulos and Mannering, 2009)), CART Techniques (see (Nambussi, Brijs and Hermans, 2008)), Artificial Neural Network (see (L. Y. Chang, 2005)), and Fuzzy Logic (see (Selvi, 2009)), which have shown the potential to be incorporated into road safety modelling.

2.8. Gaps in the Literature

There are seven major critical variables identified from the literature affecting cycling safety (Table 2.3):

a) Age,
b) Gender,
c) Environmental,
d) Road types,
e) Traffic flow,
f) Road intersections, and
g) Rider manoeuvres.

Out of these variable types, majority of the current safety models are primarily focused on road types and traffic flow only, whereas a few also include the intersection types. The rest four variables, especially age, gender, environmental conditions, and rider manoeuvres, are entirely overlooked. These may not be a significant variable for the motorists; however, these are safety, as well as mode and route choice variables. After having reviewed the literature for cycling safety, the theory behind present crash modelling, prevalent crash models and the mathematical techniques, the following gap in the literature have been identified:

"Absence of the dynamic model for the cyclists that can predict the safety based upon dynamic input variables".

The available crash prediction models generally refer to only the motorised travel in general, not specifying mode (Elvik, 2009). Peltola and Kulmala, (2010) applied TRAVA (Finnish road safety model) and found an error of -27% (underestimation) and +38% (overestimation) for the vulnerable road users. They concluded that, for understanding the relationship between flow, road conditions and the expected number of crashes, more complicated/detailed models are required. They recommended that for proper estimates of the exposure and risk estimation, advanced in-depth safety models are needed to be developed, which consider variable exposure (Peltola and Kulmala, 2010). The conventional models have been developed mainly for the assignment of motorised modes of travel and are not equipped for cyclist's special needs (Lawson, 2015). The present models cannot quantify the effect of the safety performance function and how safety is affected by the various dynamic variables. A survey by (Yannis *et al.*, 2015) found that around 70% of the European road agencies rarely or never systematically use the crash prediction model in their decision making. This is attributed to their ineffectiveness to model different travel modes with accuracy and inability to apply the models in the planning/design process (Yannis *et al.*, 2015). The present system of measuring transportation safety is quantified through the severity and frequency of the crashes that have occurred on a particular facility. However, such a measurement technique cannot be applied to a facility in the design process. As the facility has not yet been constructed, therefore there are no crash records available for this facility (Gettman *et al.*, 2008).

The present models are based on the complex human factors that are believed to be directly or indirectly responsible for the crash. The output of the prediction models is a long-term value with the main applications to forecast the yearly crash, seasonal variation, and identification of the black spots. The central assumption is that traffic flow is the direct representation of human factors responsible for these crashes. Vulnerable road users have different needs and limitations while using the road environment (Aldred, Woodcock and Goodman, 2016). It is essential to investigate the nature of the relationship between the roadway, environmental, operational characteristics, and safety to understand the mechanism involved in the crashes and to better predict the occurrence of crashes (Reurings *et al.*, 2006). Cyclist safety varies between different street types and environments, and safety models should consider this difference in exposure, which differs from one road user to another (Vagverket, 2001). Nambussi, Brijs and Hermans, (2008) review of the crash prediction models recommended that the future research of the risk analysis should consider the characteristics of traffic flow, traffic control, geometrics, driver characteristics, vehicle types and the environment characteristics (Nambussi, Brijs and Hermans, 2008).

The concept of predicting crashes in real-time is in infancy. For even motorist's real-time safety modelling is in the primitive conceptual stage. At present theoretical models are being explored, which are prone to unrealistic data requirements and lack of reliability. Also, the majority of the current motorist crash prediction models have a prediction success of less than 50%. Because of this limitation, none of the studies in the literature recommended their models to be used directly for practical applications (Hossain and Muromachi, 2009).

All the present safety models are reactive; they are not dynamic and cannot consider the dynamic nature of the cyclist interaction with variable infrastructure and quantify its safety implications. These all are based upon modelling human error, whereas the critical variables from literature are overlooked. It is because of this gap in the field of cycling safety, when US Federal HighWay Administration (FHWA) performed safety analysis using the major simulation software's, VISSIM, AIMSUM, TEXAS and PARAMICS for cyclists, output revealed that there are modelling inaccuracy in the microsimulations (Gettman *et al.*, 2008). The driver and behaviour logic in the simulation does not reflect crash avoidance under all interactions. The output in some scenarios implied a crash, whereas the simulations were not modelled for crashes. They have questioned the metrics of safety analysis performed by these micro simulations. None of these models can consider the cyclist's behaviour and limitations. The FHWA Surrogate Safety Assessment Model (SSAM) clearly pointed out the need for developing the safety index. One of the ways they recommended could be by weighting the different scenarios, frequencies and severities, and aggregating results observed from the distribution of daily traffic conditions to form a composite safety assessment of a traffic facility. This would facilitate safety assessment efforts (Gettman *et al.*, 2008). Therefore, this field of engineering needs to develop a real-time crash prediction model for cyclists, which allows the input of dynamic identified variables.

2.9. Chapter summary

In this chapter, a state-of-the-art review of the variables affecting cycling safety, crash models, and present mathematical techniques are undertaken. The study has found that there are a variety of factors that affect cycling safety. The critical variables affecting safety can be broadly classified into seven variable groups: a) Age, b) Gender, c) Environmental conditions, d) Road types, e) Traffic flow conditions, f) Road intersections, and g) Rider manoeuvres. The conventional traffic safety models are mainly developed for the assignment of the motorised modes of travel and are ill-equipped for the cyclist's unique needs. Cycling safety is an important topic, but limited studies explore the risk concerning its exposure.

The current need for the transportation system requires cycling mode share to increase many folds. The primary hurdle in the process is insufficient evidence to understand the relationship between cyclist safety and the identified parameters (TRL, 2011). Studies are primarily biased towards motorist's perspective rather than a cyclist point of view in the present literature. Calvey *et al.*, (2015) argued that these studies are not able to account for the limitations of the cyclist. For a modeller to effectively and efficiently model cyclist safety, the cyclist’s vulnerability and susceptibility to various externalities must be modelled at the nanoscopic level. Presently, limited studies have attempted to undertake such modelling to model the rider personal attributes, environmental conditions, and detailed specific infrastructure variables for safe infrastructure usage.

The micro infrastructure parameters profoundly correlate with cyclist safety (Akgun, 2019), which may not be necessarily true for motorists. The study on the usage of the cyclist's infrastructure through naturalistic research concluded that the present safety models are incapable of modelling the safety for the cyclist (Calvey *et al.*, 2015), due to the complex nature of interaction and exposure to different variables compared with the motorists. In the presently available knowledge, it is essential to develop an empirical tool for predicting safety and quantify the effect of the identified dynamic variables (their interaction, correlation, and causation) that the cyclist is subjected to while riding on the road surface in their natural built environment. This void in the literature has affected the development of recommendation measures, negatively affecting the planning and development of cycling infrastructure. Hence, the study will aim to develop cyclist-based crash models, understand, and quantify various critically identified safety variables.

Chapter 3.

Intelligent hybrid modelling framework for cycling safety and network planning/design

3.1. Introduction

This chapter proposes an intelligent hybrid modelling framework to model cycling safety. The methodology is designed with due attention to the research gap identified in Chapter 2. The methodological framework for the study is developed based upon the critique of data learning and mathematical methods. The combined hybrid approach applied in the research to meet the specific objectives is unique to the study. First, in Section 3.2, the methodological framework is presented, research methods in Section 3.3, data sources in Section 3.4, review of literature and investigation area in Section 3.5, and model developments in Section 3.6-3.9. Finally, the chapter summary is presented in Section 3.10.

3.2. Methodological Framework

The general methodological framework for the analysis of road safety are a) Traditional statistical, b) Heterogeneity, c) Causal inference, and d) Data-driven methods. There is an implicit trade-off between the prediction accuracy and understanding of the causal relationship between the critical variables in selecting any of these methods (Mannering *et al.*, 2020). The data-driven methods include various techniques such as manifold learning, machine learning, deep learning, support vector machine (SVM). K-mean, neural network, t-distributed stochastic neighbour embedding (t-SNE), and others (Maaten and Hinton, 2008; Chinesta, Keunings and Leygue, 2014). These methods have a proven application in various engineering fields due to their ability to handle a large amount of data with a high prediction accuracy (Simon Haykin, 2014). However, these methods may not provide an understanding of the mechanism of the interaction of the variables involved (Pamuła, 2016). These are, therefore, sometimes referred to as a black box.

Heterogeneity models are created to supplement existing safety models using new statistical and econometric techniques. When attempting to extract the genuine causal influence of a safety-related variable on a major safety outcome variable of interest after accounting for false associative effects or correlation effects between the variables, these models account for the potential endogeneity of the variable. Heterogeneity models are stylized in the sense that they are based on relatively small datasets with a substantially greater variety of potential endogenous and explanatory factors than publicly accessible transportation highway data. A more diverse set of variables may improve predictive capabilities and knowledge of causation; yet, greater model complexity imposes extra burdens on model transferability and predictive validation. Due to computational restrictions, model complexity also presents estimating issues. Due to the numerical integration required to capture unseen effects, they utilize simulation-based approaches or analytic approximation methods. Although significant progress has been made in such methods in recent years, the essential estimate techniques still create dimensionality issues for big accident datasets.

On the other hand, the casual-inference models are better able to identify and explain the underlying phenomenon. These are mainly times series models which identify the causal effects. However, these have been rarely used in crash modelling. These have the weak predictive capability and address a limited number of explanatory variables (Mannering *et al.*, 2020). The heterogeneity models require extensive detailed information, which may not always be available. They are complex, and their application is also quite complex. Although they can provide valuable information regarding the situation in which the crash has occurred. Still, their implementation by the front-line professionals is quite tricky, especially on a micro-level. The traditional statistical models estimate the likelihood of a crash by considering the variables, such as the number of observed crashes on an infrastructure stretch during a constant time frame. The output is usually modelled as a discrete outcome (Mannering, Shankar and Bhat, 2016). In Fig 3.1, a graphical trade-off between these methods is illustrated regarding their prediction and inference capabilities.

An ideal model for investigating road safety should uncover the causality, have a high predictive capability and be scalable to a large data set. Mannering *et al.,* (2020), in their recent work on the trade-off between prediction and causality, recommended that the future direction of research be towards developing a hybrid modelling approach. A combination of the data-driven and statistical methods while understating the causal relationship is recommended.

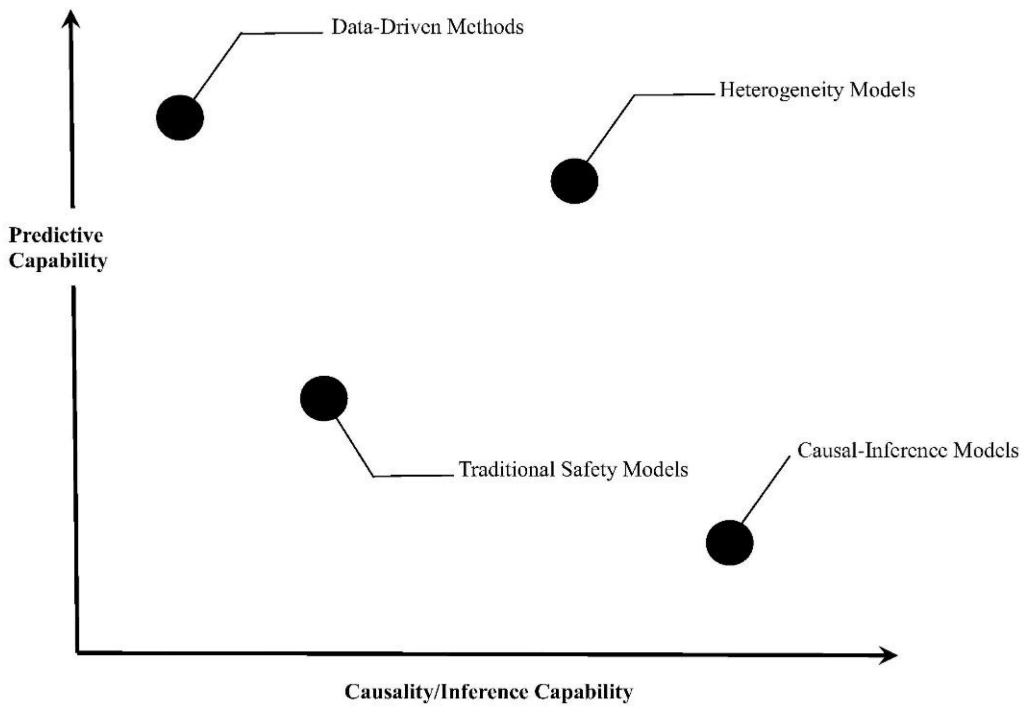


Figure 3.1. Prediction and inference capabilities of the four main methodological frameworks, (Mannering, 2018)

In this work, we propose a hybrid framework consisting of: a) Traditional Safety, b) Causal Inference, and c) Data-driven. First, the traditional statistical models are constructed using the crash and mode share rate. Then for causal inference, the heat maps are developed to understand the inference between the infrastructure and the identified safety variable. Deep learning is used to construct predictive models. The results are validated using statistical methods. Then to estimate the inference and quantify the safety performance function, standard mathematical techniques are used.

The study design consisted of the initial preparation process, a critical review of literature, data search, and making arrangements (developing research partnerships) with the relevant organisations. These included the local city councils, Department for Transport (DfT), urban observatory, Newcastle University. The methodological framework is presented in Fig. 3.2, with the primary division into the data sources,

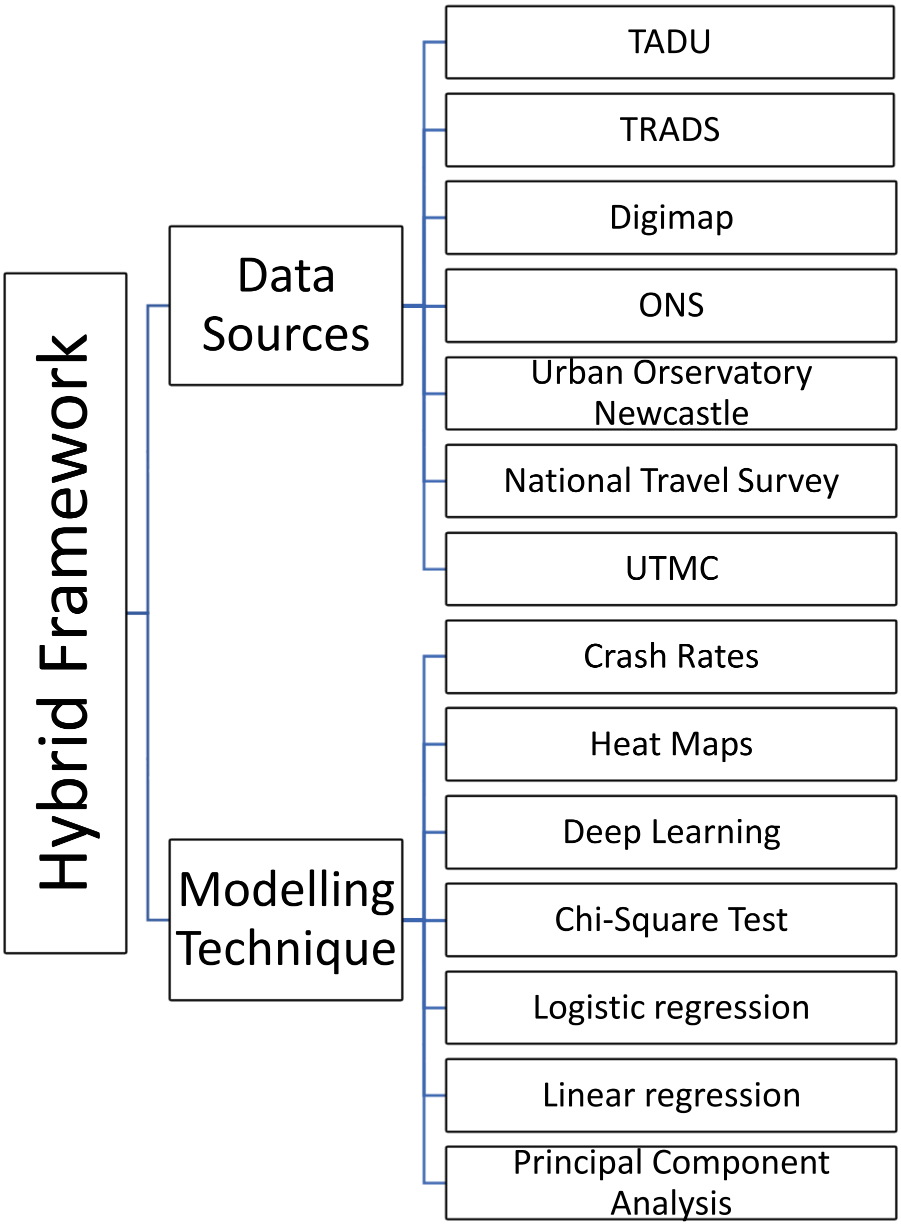


Figure 3.2. Methodological framework

and the modelling techniques used to achieve the aim optimally and efficiently. Each modelling technique, along with their selection criterion and procedure is defined in section 3.3. The following analytical steps are applied:

Step 1: A state of the art review of literature on cycling safety, current modelling theory, techniques, and models.

Step 2: Study Area for investigation: Tyne and Wear County in the North-East of England.

Step 3: Crash Database: Crash database is accessed and analysed.

Step 4: Infrastructure: Heatmaps are generated for different identified critical variables.

Step 5: Cyclist Specific variable: The base input file for age and gender variable is constructed using DfT's national travel survey.

Step 6: Environmental variables: Urban Observatory Newcastle is utilised for constructing the environmental (lighting and meteorology) input base file.

Step 7: Statistical model is constructed for different variables.

Step 8: Deep learning model is constructed to predict the safety, and variable importance is determined for each input variable.

Step 9: Statistical validation through Chi-square and Cramer V statistic.

Step 10: Mathematical modelling to identify and quantify the governing variables.

3.3. Research Methods

The primary challenge in data analysis is determining and employing the correct mathematical approach to fit the data and achieve the study's objectives. Harrell, (2001) recommended that the investigator should select an approach based upon the following five criteria (Harrell, 2001):

a) Analyses the data efficiently,

b) Fits the whole structure of the study aim,

c) Arises the problem in the dataset,

d) Appropriate for further developing

e) Extendable.

The following research methods are applied in this study to achieve different set-out objectives, fulfilling Harrell, (2001) criterion.

3.3.1. Descriptive statistics

It is challenging to visualise a large number of samples; therefore, descriptive statistics are required to comprehend the data before proceeding with any in-depth analysis. Descriptive statistics are helpful when determining statistics, including mean, median, and standard deviation. The analysis in the study started with descriptive statistics to describe the basic features of the data and an overview of the variable interaction.

3.3.2. Deep Learning

A human brain contains approximately 10^{11} neurons, which have the capability to receive, process and transmit the electrochemical signals to other neurons (Zimmermann, 1998). The term neural refers to the basic functional unit of the human nervous system. The dendrite receives the signal from other neurons; the cell body sums up all the incoming signals to generate input. Whenever the sum reaches a threshold value, the neuron fires and the signal travels down the axon to the other neurons. The axon terminals serve as the point of interconnection of one neuron with the other. The signal transmitted depends on the strength of the connections, i.e., synaptic weights (Araujo *et al.*, 2011). Humans perform a variety of complex tasks that are quite difficult to solve using the computational techniques of traditional algorithms (Zimmermann, 1998). The concept of a neural network is based upon the structure and functioning of the human brain (Nisbet, Elder and Miner, 2009). The human brain architecture is quite different from the common serial computers. The researchers of the artificial neural network aim to endow these computers with data processing abilities, resembling the functioning of the human brain (Zimmermann, 1998).

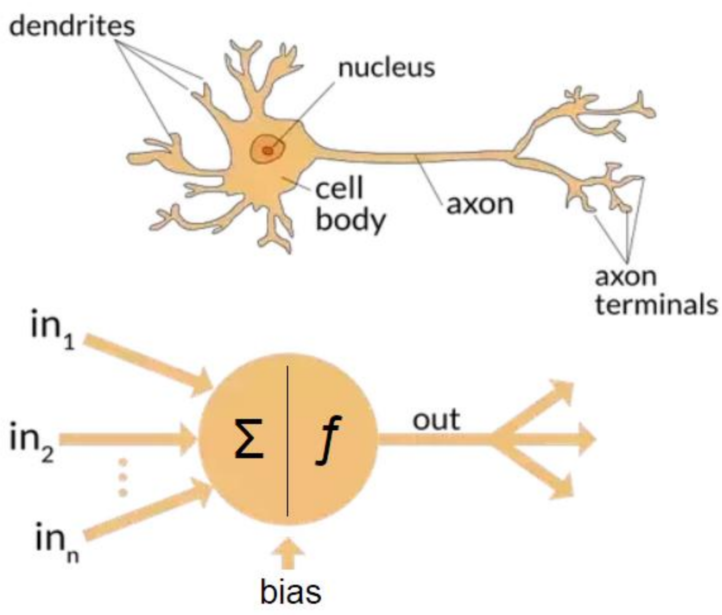


Figure 3.3. Human brain neuron and neural network

This mathematical computation technique was first proposed by (McCulloch and Pitts, 1943), in which they proposed a binary device model having a fixed activation threshold. However, the actual development of this mathematical computation method occurred in the 1980s, being developed for use with digital computers. The neural networks are massive parallel distributed processors with a natural propensity for storing experiential knowledge (IBM, 2017). This method resembles the brain in two ways:

a) The network acquires the knowledge through the learning process, and

b) The interneuron connection strengths, known as synaptic weights, are required for storing the knowledge.

An artificial Neural Network is characterised by the following system (Rumelhart and McClelland, 1986; Kasabov, 1996; Zimmermann, 1998):

a) A set of the processing elements,
b) The connectivity of these processing elements,
c) A rule of the signal propagation through the network,
d) The activation or the transfer functions,
e) The learning rules/algorithms, i.e. training algorithms, and the environment in which the network functions.

3.3.2.1. Relevance to modelling transportation

Neural networks are a prevalent class of computer intelligence models that have been widely applied for solving transportation problems. This is because they are generic, accurate and convenient mathematical models which can easily simulate the numerical model components. In Transportation science, these have been primarily used as an analytic data method because of their ability to work with substantial multi-dimensional data, modelling flexibility, learning and generalisation ability, adaptability, and good predictive ability (Karlaftis and Vlahogianni, 2011). Although there exist other algorithms and neural network is not a new concept. However, its ability to solve the complex and interchangeable system problems, which the transportation system is characterised, is the main advantage of this mathematical control technique. Gharehbaghi, (2016) proposed an artificial neural network for transportation infrastructure systems. He demonstrated its use for solving transportation problems with a case study for the periodic maintenance of the transportation network (Gharehbaghi, 2016). The neural networks for the transportation infrastructure are a multi-layer involving traditional inputs. The infrastructure problems are characterised by interconnectivity between the physical and tangible assets required for both developing and supporting the nation.

3.3.2.2. Constructing a network.

1. **Training:** When the network is presented with a set of input data and desired output, the networks self-adapts to develop the capabilities for the appropriate response from the network. This process is referred to as the training of the network.

2. **Reliability and Stability:** As these networks try to mimic the human brain, they also possess unpredictability. Therefore, it is essential to test whether the network is reliable or not. This step is undertaken by trying all the possible input variables in the variable base. However, if the amount of data to be tested is extensive, having multiple inputs, the practical assessment may become impractical. A network is stable if the learned weights minimally change as the range of the training data set increases. This is an essential property of the adaptive models, which are trained and applied in real-time. Suppose the learned weights are not in the vicinity of the globally optimum weights, then the training should be frequently repeated. It is essential to examine the convergence of the parameters.

3. **Validation of the model**: After having constructed a model, it is essential to check whether the parameters and their corresponding functions can perform their intended function or not. This verification is known as validation of the model, and this establishes the credibility of the model. There exist multiple

ways in which the performance of a trained network can be evaluated for its assessment and determination of its appropriateness. The simplest approach is the assessment of the network's performance in reproducing the training data. However, a better approach is to divide the available data set into training data for training the model and validation data for validating the trained model. A learning algorithm should be developed which splits the data into training and testing.

There is always a risk that the model parameters are overestimated, and the network may get overstrained. An overstrained model may fit the training set correctly but may not perform well on untrained data and thus have a limited or no generalisation power. On the contrary, underestimation can lead to the limited use of the predictive capabilities network (Karlaftis and Vlahogianni, 2011). A proper division is critical to ensure enough data for the learning process, and simultaneously results are assessed accurately. The recommended division in the literature is to divide the dataset 2/3 for training and 1/3 for testing, which will serve both purposes (Haykin, 2005)

3.3.2.3. Deep learning

As the relationship between the input and output gets complex, the simple neural networks may not map the input with the output effectively and efficiently. The deep networks are explored by inserting a middle layer of neurons (nodes) between the input and output nodes. Deep learning is a subset of machine learning, based on an artificial neural network in which the network's learning can be supervised, unsupervised, or reinforced. These are generally feedforward networks that can model complex non-linear relationships. The architect generates compositional models in which the object is expressed as a layered composition of primitives. As there is an additional layer, therefore weights are assigned to each connection between the input and middle nodes and between middle and output nodes. The advantages of these weights are that they have the capability to model non-linear relationships that may exist between the input and output. The number of nodes in the middle layer is directly proportional to the network's capability for recognising the non-linearity that may exist in the data set. However, by increasing the number of nodes in the middle layer, the training time increases exponentially, increasing the probability of overtraining the model. (Nisbet, Elder and Miner, 2009).

3.3.2.4 Backpropagation

Deep learning and the backpropagation learning algorithm are widely used to solve various classification and forecasting problems. The learning process of the human neuron can be roughly reflected by performing several weight adjustments. The backpropagation adjusts misclassified cases based upon the magnitude of the error predicted by the model. This adaptive process continuously iterates the models for improving the fit and the predictive power.

Steps in the Backpropagation

1. Assign the random weights to each connection.

2. Analyse the first record and calculate the values at each node as the sum of the input times their weights.

3. A threshold value is specified above which the output is evaluated to 1 and below which it is evaluated to 0.

4. Calculate the prediction error.

$$Error = Expected\ prediction - Actual\ prediction$$

5. Adjust the weight

$$Adjustment = Error \times output\ weight$$

6. Calculate the revised weight

$$Old\ Input\ weight + Adjustment$$

7. Iterate these steps based upon a specific function.

3.3.2.4 Software used

SPSS is an abbreviation for Statistical Package for the Social Sciences, which is a mathematical modelling software used by researchers. The SPSS (Statistical Package for the Social Sciences) software package was developed primarily for the management and statistical analysis of social science data, and first released by SPSS in 1968. The package has been considerably extended over the years, especially after acquisition by IBM in 2009, and is now used in all the major scientific areas. It is made up of four main programmes: a) Statistics, b) Modeler, c) Text Analytics, and d) Visualization Designer. The software offers data management capabilities, allowing researchers to do case selection, develop derived data, and file reshaping. It also provides data documentation and the ability to store a metadata dictionary. This metadata dictionary serves as a consolidated information store. Its .SAV format facilitates data extraction, manipulation, and analysis quick and straightforward. SPSS automatically sets up and imports the desired variable names, variable types, titles, and value labels using the .SAV format, making the procedure considerably easier for researchers. This makes the platform suitable for a hybrid methodology that involves using data learning as well as conventional mathematical modelling. Presently, very few platforms have such a capability to undertake hybrid modelling efficiently and effectively.

SPSS Statistics' numerous capabilities are available via pull-down menus or are written using a unique fourth-generation programming language. The advantages of command syntax programming include repeatable output, the simplification of repetitive operations, and the handling of sophisticated data manipulations and analysis. A macro language can also be used to build command language subroutines. A Python programmability extension can dynamically generate command syntax programmes by accessing information in the data dictionary and data. Furthermore, SPSS can execute any of the statistics in R due to the Python extension. It can be controlled by a Python or VB.NET application. SPSS imposes limits on internal file organisation, data types, data processing, and matching files, all of which contribute to much simplified programming. SPSS datasets are two-dimensional table structures, with rows representing instances and columns representing measurements. There are just two data types defined: numeric and text (or string). All data processing is carried out in a case-by-case manner through the file (dataset). One-to-one and one-to-many matches are possible, but many-to-many matches are not. Aside from the case-by-variable structure and processing, there is a separate matrix session where data may be processed as matrices utilising matrix and linear algebra techniques.

3.3.3. Chi-square test

A chi-square test of independence aims to determine if the observed values for the cells differ significantly from the predicted values. The chi-square statistic (Eq 3.1) is computed by summing the squared deviations divided by the expected value.

$$\chi^2 = \sum \frac{(n_{ij} - \frac{n_i n_j}{n})^2}{\frac{n_i n_j}{n}} = \sum \frac{(f_o - f_e)^2}{f_e} \tag{3.1}$$

where f_o = observed value, f_e = expected value

Along with the χ^2 statistic, a probability value is also computed. The value of p is the probability that the difference between f_o, and f_e tested by the χ^2 statistic, is due to chance. The value of $p < 0.05$ is the commonly accepted value in literature (Field, 2017)**.** In such a scenario observed value differs significantly from the expected values, and leads to infer that the two variables are not independent of each other.

The limitation of χ^2 is the inability to quantify the effect of each variable. To overcome this limitation, Pearson suggested the phi φ statistic. However, if the matrix is greater than 2 x 2, the Cramer V statistic is used. It is a post-test after the chi-square test, used for determining the significance of correlation.

$$V = \sqrt{\frac{\chi^2}{n(df)}} \tag{3.2}$$

where df is the smaller number of rows and columns.

The output is a single value, converted into a categorical value using Cohem table. It is based on the degree of freedom and the numerical V value (Cohen, 1998). Let's take the example of variables having the $df = 2$, the V values correspond to small=.07, medium=.21, and large=.35. In the similar way, the V value can be evaluated for different $df's$.

3.3.4. Polynomial Regression

Polynomial regression is a type of regression in which the relationship between the independent variable x, and dependent variable y, is modelled as an mth degree polynomial in x.

$$y_i = \beta_o + \beta_1 x_i + \beta_2 x_i^2 + \beta_3 x_i^3 \dots \dots \dots \dots \dots \dots . + \beta_m x_i^m \qquad (3.3)$$

$$i = 1, 2, \dots . . , n$$

3.3.5. Linear Regression

If the identified significant predictor is a continuous variable, interpreting the results to provide policymakers and design engineers suggestions is difficult as the predictive margins need to be calculated for any value. Therefore, linear regression is applied to interpret the influence of continuous variables, Eq 3.4 (Schneider *et.al.*, 2010).

$$y = a_0 + \sum_{i=1}^{n} a_n x_n \qquad (3.4)$$

where y is the response variable, a_0 is the coefficient of the unknowns, $a_{n,}$ = coefficient of the predictor variables, and x_n = predictor variables.

3.3.6. Logistic Regression

Logistic regression has a categorical outcome variable. The predictor variables are either continuous, categorical, or both. The predicted outcome in logistic regression is the probability of y occurring given the predictors $x_1, x_2, x_3, \dots \dots \dots x_n$. An event's probability should be between 0 and 1. Hence, the predicted outcome y should fall within this range. If the outcome value y is near to zero (0% probability), it implies that y is unlikely to occur, whereas an outcome close to one (100% probability) means that y is likely to occur (Field, 2017).

The coefficients in linear regression are adequate to describe the model; however, the coefficient in logistic regression cannot be explained by itself. As a result, when analysing the data, the odds ratio is typically employed. While coefficient estimates provide the linear equation in regression, the log of odds of the outcome provides the equation of predictors in Logistic Regression. The odds ratio is the ratio of the chances of success to the chances of failure (Agresti, 2018).

The logit function of the binary outcome variable is given below in Eq 3.5.

$$logit\ (p) = \log(odds) = \log(\frac{p}{1-p}) = a_0 + \sum_{i=1}^{n} a_n x_n \tag{3.5}$$

where a_0 is the coefficient of the unknowns, $a_{1,} a_2, a_3 \dots \dots\ a_n$ are the coefficient of the predictor variables, and $x_1, x_2, x_3 \dots \dots . . x_n$ are the predictor variables

3.3.7. Principal Component Analysis

The principle component analysis (PCA) is a mathematical technique that groups several variables into a number of dimensions, known as principal components. The variables in PCA are classified into factors, each of which has a loading level that indicates the statistical importance of the variables in that factor. A rotation matrix represents the loadings of variables in factors. The goal of the rotation is to achieve the fewest number of components while increasing the weights of the variables. There are two types of rotations (Rummel, 1988):

a) Oblique: not rotated through 90°. Oblique rotation is employed when the variables are significantly correlated with one another. It is based on coordinates, which are the primary axes and reference axes.

b) Orthogonal: 90° rotation. If no statistically significant connection exists between the variables, orthogonal rotation should be used.

The PCA is based upon two assumptions a) non-existence of multi-collinearity and b) correlation within the input variables. The correlation matrix's determinant is used for checking the first assumption (should be > .00001). The literature (Bartlett, 1950; Hair *et al.*, 2010) has recommended the use of goodness of fit metrics, Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (Eq 3.6) and Bartlett's test of sphericity (Eq 3.7) to investigate PCA's reliability. The *KMO* value varies from 0 to 1, and if the *KMO* value is less than 0.5, the dimension reduction result is invalid. Bartlett's test determines the statistical significance of the correlations in the correlation matrix.

$$KMO = \frac{\sum_{i\neq j} r_{ij}^2}{\sum_{i\neq j} r_{ij}^2 + \sum_{i\neq j} a_{ij}^2} \tag{3.6}$$

where, r_{ij} is the correlation matrix, and a_{ij} is the partial covariance matrix

$$\chi^2 = \frac{(N-k)\ln V_a^2 - \sum_{i=1}^{k}(n_i - 1)\ln V_i^2}{1 + \frac{1}{3(k-1)}(\sum_{i=1}^{k}\left(\frac{1}{n_i - 1}\right) - \frac{1}{N-k})} \tag{3.7}$$

where k is the number of samples with a sample size n_i and sample variance V_i^2, $N = \sum_{i=1}^{k} n_i$, and $V_a^2 = \frac{1}{N-k}\sum_i (n_i - 1) V_i^2$, i.e. the pooled estimate of the variance.

3.4. Data Sources

The following data sources are used in the study:

a. Crash Database,

b. TRADS

c. Digimap

d. National Travel Survey

e. Office of National Statistics (ONS)

f. Urban Observatory Newcastle

g. Urban Transport Management Control (UTMC)

3.4.1. Crash Database

The UK STATS 19 police record of the cyclist causalities are accessed from the Traffic and Data Unit (TADU), developed using the Captia Innovation Road Traffic Accident System (CIRTAS). The Gateshead council holds it for the northeast of England. The dataset has the crash record of the Tyne and Wear County from 1998. However, for modelling only data from 2005-2018, was used. Earlier data set was not used as the infrastructure, or the traffic flow conditions could have significantly changed from 2018. The dataset includes:

a. Type of severity,

b. Time, date, and location of the crash,

c. Environment conditions such as lighting conditions, weather, road surface condition

d. Sociodemographic information such as age and gender,

e. Contributory factors,

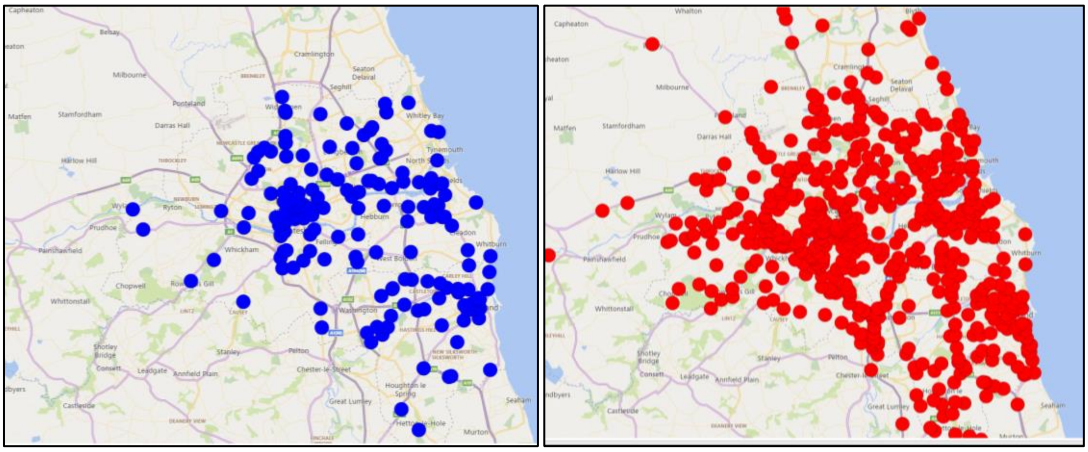
f. Vehicle manoeuvre and movement,

g. Overview of infrastructure present,

h. Brief summary of the crash as reported by the police.

3.4.2. TRADS

The flow characteristics for the study area is obtained from the TRAffic flow Database System (TRADS). Through this system, the traffic cameras and counters are accessed. The flow modelling was performed from 1st Jan-31st Dec, 2019.



a) b)

Figure 3.4. Overview of the a) Cyclist flow cameras and b) Motor vehicle cameras in the study area

3.4.3. Digimap

It is an online map and data delivery service which is available to the research group. EDINA operates it at the University of Edinburgh. This platform is used to extract the infrastructure information based upon the WGS84 coordinates obtained from TADU for a crash. This platform hosts accurate infrastructure maps depicting the present as well as past conditions. This ensures that exact infrastructure parameters are used for modelling based on the crash's temporal conditions rather than the present conditions. The following infrastructure information is extracted for each crash:

a. Type of infrastructure,
b. Number of lanes of traffic,
c. Junction details,
d. Various transportation controls,
e. Special treatments such as bespoke cycling infrastructure, shared bus-cycleway, and others.

3.4.4. National Travel Survey

The DfT's national travel survey (NTS) is a household survey to monitor the long-term trends in personal travel and inform the development of policies. It is the primary source of data on personal travel patterns for England. The data is collected from household interviews and trip diaries.

3.4.5. Office of National Statistics (ONS)

ONS is responsible for collecting and publishing statistics relating to the economy, population, and society at national, regional, and local levels. It is an independent body, which reports directly to the UK parliament.

3.4.6. Urban Observatory Newcastle

Newcastle university's urban observatory collects over 50 types of data from historical meteorological to real-time sensory data. It is the largest sensor deployment in the UK with over 1,000 sensors, 2,000 observations each minute, and holds 900 million observations. It is funded by Newcastle University in partnership with UK collaboration for research on infrastructure and cities (UKCRIC). The lighting and meteorological conditions in the study area are evaluated and modelled using the said data from the sensors.

3.4.7. Urban Transport Management Control (UTMC)

The Tyne and Wear urban transport management control (UTMC) is a partnership between the five local authorities of Tyne and Wear, with the Newcastle city council being the lead authority. The system combines the different intelligent transport systems into a single platform. The system integrates air quality stations, parking guidance systems, street works database, and automatic number plate recognition systems.

After obtaining access to the concerned platforms, further study was initiated. The study was primarily divided into six stages; state of the art review, analysing the study area, modelling age variable, modelling gender, modelling environmental conditions, and modelling the micro-infrastructure variables. The appropriate applicable approaches are described in the corresponding sections.

3.5. State of the art review of literature and investigation area

The overview of the methodological framework, appropriate research methods, and the data sources are explained in previous sections. The research methods included descriptive statistics, deep learning neural networks, chi-square test, Cramer V, linear regression, logistic regression, and principal component analysis. These are identified as appropriate methods to establish, model and develop the understanding of the critical variables affecting cycling safety in its natural environment. In the following sections, the step-by-step hybrid approach for each stage is described. These describe the data, how it was collected and modelled.

In Section 3.6, the model developed for the age variable is presented, followed by gender modelling in Section 3.7. The model developed for the varied environmental conditions is presented in Section 3.8, and micro-infrastructure variables in Section 3.9.

3.5.1. State of the art review

The study design started with a state-of-the-art review of the literature to understand cycling safety, investigate the critical variables affecting the safety, and present safety models. This helps to identify the research gap and formulate global aim and objectives. The review aims to appraise the relevant research in this field critically. A systematic review along with a three-step review process is employed. Firstly, academic databases are searched (Scopus web of science, Google scholar, CEDB, ProQuest, science direct, safety science, accident analysis and prevention, platforms such as Research Gate and Universities Transport Studies Group (UTSG), and others). Also, Northumbria and Newcastle University library searches are utilised (offline as well as online). The databases are searched for the relevant literature with no limitation to the year of publication or contexts such as transport, industry, health, or mobility. The following search terms are used:

a) Sustainable transportation,

b) Cycling safety,

c) Cycle traffic,

d) Transport safety or crash,

e) Crash models,

f) Mathematical modelling, and

g) Mobility as a service.

A good number of articles and reports are collected in this process, followed by the screening process. Only the abstracts are read in this step. Then the selection is made based upon qualitative analysis. The third step involves reviewing the complete article and then documenting the same in word and excel. This process was iterated till the completion of the study.

3.5.2. Study Area

The study area of Tyne and Wear county was selected for investigation. An overview of the analysis performed in the study area along with the data sources and operations, is illustrated in Table 3.1.

Table 3.1. Analysis performed in investigation chapter

Y	x	Data source	Operation
Traffic flow	Monthly variation	TRADS	Polynomial regression, Flow rate, Flow type: non-peak, interpeak, and peak
	Hourly variation	TRADS	Polynomial regression, Flow: yearly, average hourly, Flow rate, Flow type: non-pear. Inter peak, morning peak, and evening peak
	Daily variation	TRADS	Flow, Flow rate
Lighting conditions	Month	Urban observatory	Polynomial regression, Lighting hours,
	Flow	Urban observatory	Polynomial regression, Flow, Flow rate

Meteorological conditions	month	Urban observatory	Precipitation in mm
Personal attribute: Age	Gender	NTS, and ONS	Trips per person, Trip rate, Miles per person, Mile rate, Male/Female ratio
Crashes	Hour	TADU	Frequency, Crash Rate
	Day	TADU	Frequency, Crash Rate
	Month	TADU	Frequency, Crash Rate
	Lighting	TADU and Urban observatory	Frequency, Crash Rate
	Meteorology	TADU and Urban observatory	Frequency, Crash Rate
	Road Surface condition	TADU	Frequency, Crash Rate
	Age	TADU	Frequency, Crash Rate
	Gender	TADU	Frequency, Crash Rate
Crashes	Speed limit	TADU and Digimap	Frequency, Crash Rate
	Carriageway location	TADU and Digimap	Frequency, Crash Rate
	Number of vehicles involved	TADU	Frequency, Crash Rate
	Roadway type	TADU and Digimap	Frequency, Crash Rate
	Functional road classification	TADU and Digimap	Frequency, Crash Rate
	Intersection type and control	TADU and Digimap	Frequency, Crash Rate
	Rider Manoeuvre	TADU and Digimap	Frequency, Crash Rate

The following analysis is performed in the study area.

3.5.2.1 Traffic flow variation

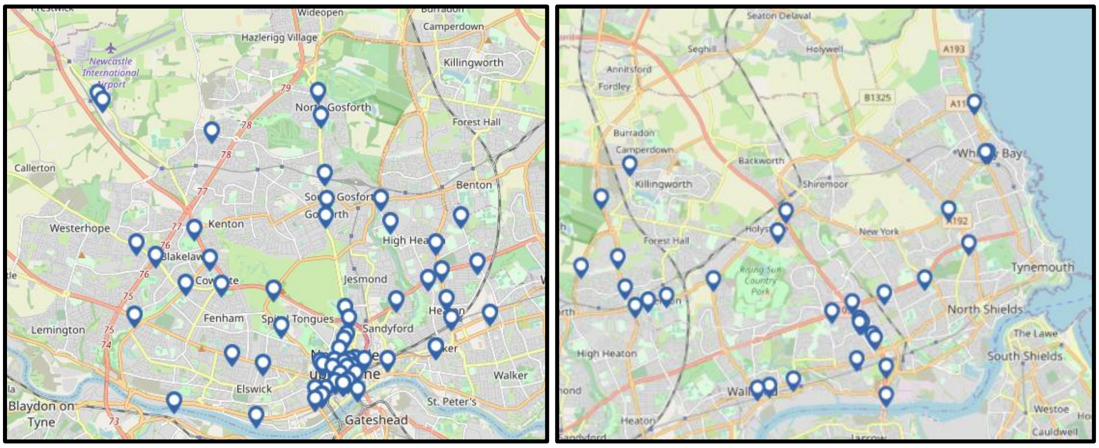
The traffic cameras and counters (TRADS) are used to evaluate the traffic flow conditions. The traffic flow is measured from 1st January to 31st December. A total of 365 traffic cameras and counters in the study area, having 15-minute data frequency, are used for developing the base input file. There are following three types of externalities that need to account for:

a) Roadworks: modelled through UTMC, Tyne and Wear,

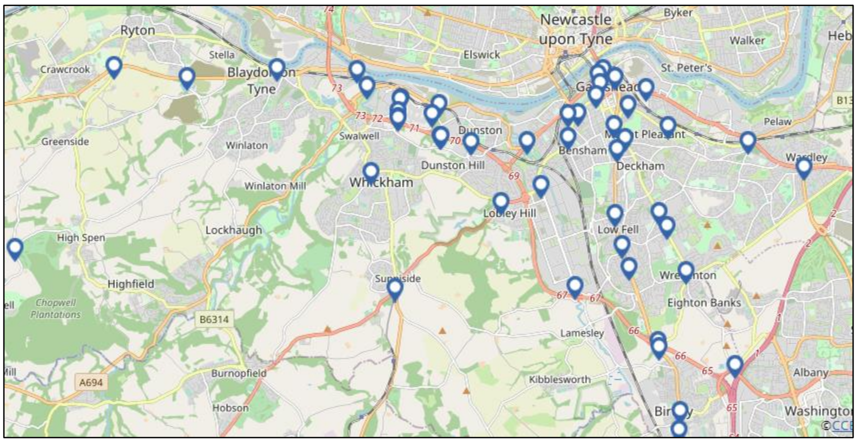
b) Crash: modelled through TADU

c) Maintenance: modelled through Gateshead council

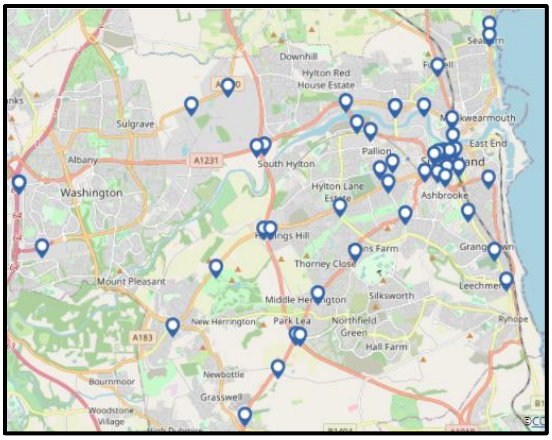
In all three externalities, the data was removed from the dataset to maintain accuracy and efficacy. A base input file is constructed, having detailed information regarding the flow in the study area. This is then followed by descriptive analysis and polynomial regression to uncover the information regarding the temporal and spatial variation of the infrastructure by the users.



a) b)



c)



d) e)

Figure 3.5. The overview of the traffic cameras (2019) in a) Newcastle, b) North-Tyneside, c) Gateshead, d) South Tyneside, and e) Sunderland

3.5.2.2 Environmental conditions variation

The detailed variation of environmental variables in the study area is obtained from the urban observatory. The lighting conditions are codded based upon the sunrise (18^0 sun angle) and sunset; the same criterion used by the city council to operate the streetlights. The following classification is used:

a) Light (L = 1),

b) Dark (L = 0), and

c) Intermediate state: (L = (0-1)) depending upon the duration in an hour having sunlight, e.g. for 30 minutes sunlight in an hour, L = 0.5.

The meteorological conditions are measured through the rainfall depth in millimetres (mm), measured by the urban observatory. The mm values are directly used in modelling.

3.5.2.3 Personal attribute of the rider

The usage of the infrastructure by age and gender is determined using the national travel survey. The ONS data is used to determine the proportion of people belonging to the said age and gender group in the study area. The detailed information regarding the infrastructure usage based upon age and gender is determined through descriptive statistics based upon these two datasets.

3.5.2.4 Temporal and spatial variation of crashes

To gain an overview of the spatial and temporal variation of the crashes, descriptive analysis is performed on the crash base file, combined with meteorology and lighting data.

3.5.2.5 Infrastructure variation of crashes.

The crash base file is coupled with the Digimap through descriptive analysis to obtain detailed information regarding the variation of crashes with different infrastructure types. The coordinates from TADU are inputted into Digimap, and a data request is sent to EDINA. An infrastructure data file is then sent back by EDINA, having the requisite infrastructure features that were present at the time of crash rather than the present features. This procedure is iterated for each crash, and a base input file is constructed.

3.6. Model development for the age variable

The analytic procedure applied in modelling the personal attribute of rider age is presented in Table 3.2.

3.6.1. Traditional safety model and heatmap

Firstly, the age distribution for each sub group is determined through the ONS survey. Then using the national travel survey, the miles per person is determined, followed by calculating the total miles traversed by the particular age groups. Similarly, the crash frequency for each group is determined using the crash base input file. A base input file is constructed, having all the required information for each identified age group. Then, both crash and mile rates are compared and modelled to obtain the risk faced by each rider group (for the same distance traversed). The normalised risk is determined for each subgroup concerning the safest sub-group for comparing the variables within themselves. The analysis is performed accurately up to one decimal place. The particular risk and normalized risk concerning the safest age group is estimated through the following equations.

$$R = \frac{C}{M_M} \tag{3.8}$$

$$N_R = \frac{R_G}{R_S} \tag{3.9}$$

where R = risk, C = crash frequency, M_M = million miles traversed, N_R = normalised risk, R_G = risk of the modelled group, R_S = risk of the safest age group.

Table 3.2. Analytic methodology used for modelling the rider age

Step	Variable modelled	Output modelled
Traditional safety model	Miles per person, Total million miles traversed Crash frequency	R = Risk = crashes/ million miles traversed N_R = normalised risk = group risk/risk of the safest group
Heat maps	WGS84 coordinates of each crash	Heatmaps
Deep learning neural network	Input variables of a) Infrastructure b) Spatial c) Personal attributes d) Environment	Predictive riskiest age group, evaluated through: a) ROC curves b) AUROC values c) Gain chart d) Lift chart
Variable importance	a) Importance b) Chi-square statistic c) Cramer V	a) Normalised importance (% age) b) Statistical association c) Degree of association
Linear regression	a) Spatial variables b) Infrastructure c) Exact flow rate d) Exact precipitation in mm, and number of lighting hours	a) Linear regression equation b) Standardised coefficient

To obtain detailed information concerning the crash site's infrastructure, WGS84 coordinates of each crash are extracted from TADU. These coordinates are recorded as accurately as possible, as it serves as the basis for further legal and other courses of actions. Then, to investigate how different infrastructure poses a varying risk to different riders, heat maps are generated, providing insight into the usage of infrastructure.

3.6.2. Deep Learning neural model

In the first step of model development, a learning algorithm is developed to divide the data set randomly into training (65%), validation (30%), and testing (5%). The data set is based upon real life data that is obtained from data sources (section 3.4), as the aim is to undertake modelling with direct practical applications. This division ensures proper learning of the constructed model, assesses the trained model and ensures that the constructed model is relevant to untrained scenarios (Zimmermann, 1998; Haykin, 2005). For random division, Bernoulli distribution is used. The predictive safety model is developed using four input variable types: a) Infrastructure, b) Spatial, c) Personal, and d) Environmental input variables (Table 3.3).

Table 3.3. Input variable for constructing a predictive model

No.	Input Variable	Values
1.	**Infrastructure**	
a).	Speed limit (maximum permissible speed limit on the road).	20-70.
b).	1st Road class (for intersections, the rider may be required to move from one hierarchy level of road classification to another. This is the first hierarchy classification of the road from which the rider is moving towards the next one).	A, B, C, E, U.
c).	2nd Road class (hierarchy classification of the road that the rider to intending to move to / already moved to).	A, B, C, E, U.
d).	Junction detail (type of intersection).	Crossroad, Mini Roundabout, Multiple Junction, Straight Road, Roundabout, Slip Road, T or Staggered, Private Drive.
e).	Junction control (type of control employed at the intersection).	No Control, Traffic Signal, Give way or uncontrolled, Stop sign.

f)	Vehicle manoeuvre (manoeuvre that rider was performing/intending to perform when the crash occurred).	Changing lanes, Going ahead, Moving off, Overtaking, Parked, Reversing, Slowing/stopping, Turning, U-turn, Waiting to go ahead, waiting to turn.
g)	Carriageway hazard (additional unexpected hazards on the carriageway).	Animal in the carriageway, Dislodged vehicle load on the carriageway, None, Object in the carriageway, Pedestrian on the carriageway.
h)	Road type (type of road infrastructure present at crash spot).	Dual Carriageway, One-way street, Roundabout, single carriageway, slip road.
i)	Vehicle junction location (location of cyclist at the junction when crash occurred).	Approaching junction or waiting/parked at junction exit, cleared junction or waiting/parked at junction exit, Entering, Leaving, Mid Junction, Straight Road (Not at or within 20 meters of the junction).
j)	Road location of vehicle (location of cyclist to the road infrastructure when crash has occurred).	Bus Lane, Busway, Cycle lane, cycleway, footpath, on layby or hard shoulder, main carriageway, tram/light rail track.
k)	Skidding and overturning (post-crash whether there was any skidding or overturning).	No skidding or overturning or jack-knifing, overturned, skidded, overturned, and skidded.
l)	Special site conditions (any infrastructure defects at crash location).	Defective Traffic Signal, None, Oil, mud, defective road signs or marking, defective road surface, roadworks.
2.	**Spatial**	
a).	Journey hour (hour in which crash occurred)	0-23.
b).	Number of vehicles (Number of vehicles involved in the crash).	1-5.
c).	Month of Journey (month in which crash occurred).	Jan-Dec.

d)	Journey Day (day of week on which crash occurred. The day, month and hour of journey are a representation of the traffic flow regime plying at the time of the crash)	Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday.
3.	**Personal attributes**	
a).	Gender (rider gender).	Male, and Female.
b).	Breath Test (to check whether rider was intoxicated or not).	Negative, Positive and Not Required.
c).	Journey Purpose (the purpose of journey being undertaken).	Commuting, work trip, School Journey by Pupil, taking pupil to school, other.
4.	**Environmental**	
a).	Lighting conditions (the lighting conditions, and presence and working of streetlights).	Daylight /Darkness- No Street Lighting, Street Lighting Unknown, Street Lights present and lit, Street Lights present but unlit.
b).	Meteorological conditions (the meteorological conditions when the crash occurred).	Fine/Rain/Snow-with high winds, without high winds, fog, or Mist Hazard, Other.
c).	Road surface condition (the road surface condition at the time of the crash. The road surface and meteorological conditions may not necessarily be the same).	Dry, Frost/ice, Wet/damp, Snow.

Table 3.4. Output variable for constructing a predictive model

No.	Output Variable
1.	0-16
2.	17-24
3.	25-34
4.	35-44

5.	45-54
6.	55-64
7.	Over 65

Considering that relationship between input variables and output is highly non-linear and complex (Elvik, 2009); therefore, two hidden layers are used in the network. The batch training, cross-entropy error function, and scaled conjugate gradient optimisation are used. The network structure is explicitly defined in Table 3.5.

Deep learning trains itself on the training data to map the input with the output through weighted connections between different layers, like the normal functioning of a neuron in the human brain. The neural network consists of neurons grouped into different interconnected layers of input, hidden and output layers. The neurons from one layer interact with neurons from other layers through weighted connection, a real number signifying association's strength and relationship. The networks learn to map the given input with the output and perform non-linear mapping of a higher differential order through these weighted connections, which cannot be undertaken using simple conventional mathematical theories.

A four-step iterative learning process is employed for modelling. The signal is transmitted within the network through the activation function; identical to the signal transmission between two brain neurons in the synaptic cleft. Initially, random weights are assigned between the input and hidden, first and second hidden, and hidden and output layer. As weights are randomly assigned, an expected error is modelled using

Table 3.5. The network structure of the deep learning model

	Number of hidden layers	2

Network Topology	Elements in each layer	350
	Activation function between the hidden layers	Hyperbolic Tangent
	Activation function between hidden and output layer	SoftMax
Training	Type of Learning	Supervised
	Optimisation	Gradient Descent (Batch)
	Iterative Method	Scaled conjugate gradient
	Initial Lambda	10^{-9}
	Initial Sigma	10^{-9}
	Initial Centre	0
	Initial offset	$\pm 10^{-9}$
Stopping and Memory Criterion	Steps (maximum) without a change in the error	999,999
	Training (maximum) time	999,999
	Training (maximum) epochs	999,999
	Relative change in the training error (minimum)	10^{-6}
	Relative change in the training error ratio (minimum)	10^{-6}
	Cases to store in the memory (maximum)	999,999

the cross-entropy (*E*) error function. The initial weights (*w*) are then updated based upon this error through the backpropagation algorithm (Eq 3.12-3.15). The weighted connection w_{hi} (Eq 3.15-3.16) is updated in every new training epoch by adding it to the previously updated weight. This process is iterated using scaled conjugate gradient optimisation (Eq 3.17-3.22).

Step 1: Random weights and Activation: Firstly, between each connection, i.e. input and hidden, within hidden layers, and hidden and output layer, random weights are assigned. For signal transmission between the synaptic cleft activation function 'Hyperbolic tangent' (Eq 3.10) for hidden layers and 'Softmax' (Eq 3.11) for the output layers is used.

$$A_i = \tanh(F_i) = \frac{e^{F_i} - e^{-F_i}}{e^{F_i} + e^{-F_i}} \tag{3.10}$$

$$A_i = \sigma(F_i) = \frac{e^{F_i}}{\sum_{j=1}^{k} e^{F_j}} \tag{3.11}$$

where A_i is the activation of the ith output neuron, k is the number of output neurons

Step 2: Error modelling: Cross entropy error function is used to model the error between the output obtained and the desired output.

$$E = -\sum_{i=1}^{k} t_i \ln O_i \tag{3.12}$$

where O_i is the actual output obtained for the output node j, and t_i is the largest value of i.

Step 3: Synaptic weight update: The randomly assigned synaptic weights are updated based on the error obtained in Eq 3.12. The backpropagation algorithm calculates the gradient of the training error in each training case (epoch).

i) nodes between the input and hidden layer

$$\frac{\partial E}{\partial w_{hi}} = \sum_{i=1}^{m} \left(A_i - t_j\right) x_h w_{hi}(1 - x_h) x_k \tag{3.13}$$

ii) nodes between the output and hidden and layer

$$\frac{\partial E}{\partial w_{hi}} = (A_i - t_j)x_h \tag{3.14}$$

After error calculation, the weight (w_{hi}) is updated in each epoch by adding it to the previously updated weight

$$\Delta\, w_{hi} = -\gamma \frac{\partial E}{\partial w_{hi}} \tag{3.15}$$

$$\Delta\, w_{hi+1} = w_{hi} + \Delta\, w_{hi} \tag{3.16}$$

where γ is the learning rate, and *x* is the input variable

Step 4: Scaled conjugate gradient learning: The above steps are continuously repeated (iterated) until either the maximum number of these iterations (epochs) or minimum training error change is achieved.

$$d_0 = r_0 = b - Ax_o \tag{3.17}$$

$$\alpha_i = \frac{{r_i}^T r_i}{{d_i}^T A d_i} \tag{3.18}$$

$$x_{i+1} = x_i + \alpha_i d_i \tag{3.19}$$

$$r_{i+1} = r_i - \alpha_i A d_i \tag{3.20}$$

$$\beta_{i+1} = \frac{{r_{i+1}}^T r_{i+1}}{{r_i}^T r_i} \tag{3.21}$$

$$d_{i+1} = r_{i+1} + \beta_{i+1} d_i \tag{3.22}$$

where *a* and *b* are constants.

The performance of the constructed predictive model is evaluated through the Area under the Curve (AUC) of the Receiver Operating Characteristics (ROC). This is the evaluation matrices, which is an effective measure of the accuracy of a constructed network (Hajian-Tilaki, 2013). ROC is a probability curve, and AUROC represents the measure of the separability power of the network. While calculating the risk, the higher the AUROC value, the better the network's distinguishable power. Besides, gain and lift charts are used for qualitative evaluation, the visual aids for evaluating the performance, which asses the model's predictive capability compared with a non-model-based probability evaluation. After model construction and performance measurement, the next step is to validate the model through validation datasets. This process ensures an unbiased evaluation of the model fit on the training dataset while tuning the model hyperparameters; followed by checking the model's performance on unseen data providing an unbiased evaluation of the final developed predictive model.

3.6.3. Variable importance

The critical variables in the data learning model are identified through variable importance. Each variable's normalised importance concerning the most critical variable is also evaluated to compare variables relative to each other. This is based upon both testing and validation data sets. The independent variable importance measures how much the predicted output value changes, viz a viz change in the input variable. Each input variable's normalised importance is their respective importance value divided by the largest importance value and expressed as percentages.

After developing the predictive model, the statistical validation of the identified critical variables is undertaken. The input variables affecting the crashes are measured either on a nominal or ordinal scale. Therefore, the non-parametric technique is the ideal statistical method in such scenarios, especially when the sample size is small. The two assumptions of: a) Samples being random, and b) Observations being independent of each other (Pallant, 2011) need to be met. The crashes are a random phenomenon (Environment and Transport Overview and Scrutiny Committee, 2015) and are independent of other crashes occurring at different locations, thereby satisfying the two pre-requisites. Chi-square test for goodness of fit, a non-parametric technique specifically designed to solve such complex non-linear problems, tests whether there exists a relationship between two variables and uses the sample data to test the hypothesis regarding the shape of the proportion of population distribution. It determines how well obtained sample proportions fit the population proportion specified by the null hypothesis. Each variable in the sample is classified on n variables, creating an n-dimensional frequency distribution matrix. As the matrix is greater than two by two order, a modification of the Phi-Coefficient, known as Cramer V, is used to measure the strength of association (Cohen, 1998). The following four-step procedure is employed:

Step 1: Chi-square statistic is calculated.

Step 2: Degree of freedom of the two variables, whose association being evaluated is calculated.

Step 3: For determining the strength of the correlation, Cramer V statistic is used, a post-test (after Chi-square correlation test):

Step 4: Cramer V is a single-valued numeric output, which needs to be converted into qualitative knowledge, performed using Cohen's table. This determines the strength of correlation using the degree of freedom and the numerical V value, in terms of no correlation, small, medium and large correlation (Cohen, 1998).

3.6.4. Linear Regression

As age is a continuous variable, therefore linear regression is used. The nominal variable types are avoided, such as the month of travel, infrastructure parameters. Instead, a better representation of these conditions, such as monthly flow rate, monthly precipitation, and lighting conditions, is used. These variables are not modelled in the deep learning model. The predictive modelling aims to develop an interoperable model for different situations that can be interoperable to different traffic flow conditions, environmental and infrastructure conditions through a simple validation process. To understand the variable interaction and how these variables affect safety (in a varied way), these location-specific variables of exact rainfall data, lighting hours are used rather than the quantitative definition of the lighting or metrology used in the deep learning model.

3.7. Model development for gender variables

The analytic procedure applied in modelling the personal attribute, rider gender is presented in Table 3.6.

3.7.1. Traditional safety model and heatmaps

A similar methodology as that of 3.6.1, is employed. A base input file is constructed, having all the required information for each identified sub-group of age and gender. Then, both crash and mile rates are compared and modelled to obtain the risk faced by each rider group (for the same distance traversed). The normalised risk is determined for each subgroup concerning the safest sub-group for comparing the variables within themselves.

Table 3.6. The analytic methodology used for modelling the rider age

Step	Variable modelled	Output modelled
Traditional safety model	a) Miles per person, b) Total million miles traversed c) Crash frequency	a) R = Risk = crashes/ million miles traversed b) N_R = normalised risk = group risk/risk of the safest group
Heat maps	a) WGS84 coordinates of each crash b) Age distribution	a) Heatmaps b) ANOVA c) Scheffe test
Deep learning neural network	Input variables of a) Infrastructure b) Spatial c) Environment	Predictive riskiest age group, evaluated through: a) ROC curves b) AUROC values c) Gain chart d) Lift chart
Variable importance	a) Importance b) Chi-square statistic c) Cramer V	a) Normalised importance (% age) b) Statistical association c) Degree of association
Logistic regression	a) Hourly flow rate, b) Traffic flow regime c) Environmental conditions d) Rider age e) Exact precipitation in mm, and number of lighting hours	a) Regression equation b) Odds ratio.

To investigate how different infrastructure poses a varying risk to different riders, heat maps are generated, providing insight into infrastructure usage. The results from the heat maps are validated statically through Analysis of Variance (ANOVA). ANOVA is an omnibus test, which measures whether the safety of different infrastructures depends on age, based upon the assumption of homogeneity of variance tested through Levene statistic (*W*).

$$W = \frac{(N-k)}{(k-1)} \cdot \frac{\sum_{i=1}^{k} N_i \, (\overline{Z_{i.}} - \overline{Z}_{..})^2}{\sum_{i=1}^{k} \sum_{j=1}^{N_i} (Z_{ij} - \overline{Z}_{i})^2} \tag{3.23}$$

where $Z_{ij} = \left| Y_{ij} - \overline{Y_i} \right|$, Y_i is the mean or median of the ith sub-group, Y_{ij} is the measured variable of the jth case for the ith group, *N* is the sample size, *k* is the number of sub-groups, $\overline{Z_i}$ are the group mean of Z_{ij}, and $\overline{Z}_{..}$ is the overall mean of Z_{ij}.

To investigate the effect of individual infrastructure type, the post hoc (Latin meaning after that, implying after omnibus test) comparison; Scheffe test (*S*) is used.

$$S = \sqrt{(k-1) f_{-value} \, MSE \, \left({}^{1}/_{n_i} + {}^{1}/_{n_j} \right)} \tag{3.24}$$

where *k-1* is the degree of freedom within the sample groups, f_{-value} is the obtained value of *f*, MSE is the mean square error from ANOVA, n_i and n_j are the sample size of the *ith* and the *jth* sub-group, respectively.

3.7.2. Deep learning neural model

There are six (three each for male and female) different deep learning constructed, using the three types of input of spatial, environment and infrastructure variables (Table 3.7). The output variables that each of these models can take are described in Table 3.8.

Table 3.7. Input variable for the gender predicted models

No.	Input Variables	Values
1.	**Spatial**	
a)	Month of journey	Jan-Dec.
b)	Journey day	Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, and Sunday.
c)	Journey weekday/ weekend	Weekday, and Weekend.
d)	Journey hour	0-23.
e)	Number of vehicles	1-5.
f)	Journey purpose	Commuting, work trip, School Journey by Pupil, taking pupil to school, Other, and Unknown.
2.	**Environmental**	
a).	Lighting conditions	Daylight /Darkness- No Street Lighting, Street Lighting Unknown, Street Lights present and lit, and Street Lights present but unlit,
b).	Weather (meteorological) conditions	Fine/Rain/Snow-with high winds, without high winds, fog, or Mist Hazard, and Other.
c).	Road surface condition	Dry, Frost/ice, Wet/damp, and Snow
3.	**Infrastructure**	
a)	Road type	Dual Carriageway, One-way street, Roundabout, Single carriageway, and Slip road,
b)	Speed limit	20-70
c)	1st Road class	A, B, C, E, and U
d)	Road hierarchy level	0-4
e)	Road hierarchy level and direction	-4 to 4

f).	Junction detail	Crossroad, Mini Roundabout, Multiple Junction, Straight Road, Roundabout, Slip Road, T or Staggered, and Private Drive
g).	Junction control	No Control, Traffic Signal, Give way or uncontrolled, and Stop sign
h)	2nd Road class	A, B, C, E, and U
i)	Vehicle manoeuvre	Changing lanes, Going ahead, Moving off, Overtaking, Parked, Reversing, Slowing/stopping, Turning, U-turn, Waiting to go ahead, and Waiting to turn
j)	Vehicle junction Location	Approaching junction or waiting/parked at junction exit, cleared junction or waiting/parked at junction exit, Entering, Leaving, Mid Junction, Straight Road (Not at or within 20 meters of the junction)
k)	Road location of vehicle	Bus Lane, Busway, Cycle lane, cycleway, footpath, on layby or hard shoulder, main carriageway, tram/light rail track
l)	Skidding and overturning	No skidding or overturning or jack-knifing, overturned, skidded, Overturned and Skidded

Table 3.8. The output of the gender predictive models

Male predictive model	0-16 Male	17-24 Male	25-34 Male	35-44 Male
	44-54 Male	55-64 Male	over 65 Male	
Female predictive model	0-16 Female	17-24 Female	25-34 Female	35-44 Female
	45-54 Female	54-64 Female	Over 65 Female	

The same network structure, as described in section 3.6.2., and 3.6.3. is used for model development and variable importance.

3.7.3. Logistic regression model

As the gender of the rider is an ordinal variable, therefore, logistic regression is used. The model development is performed using the specific input variables. To understand variable interaction and investigate how these variables affect safety for a particular gender, additional location-specific variables of exact traffic flow, rainfall data, and lighting hours are used, rather than the quantitative variables representing these conditions. To facilitate the development of a regression model and quantify the impact of the input variable concerning the ordinal gender variables, the input variables are numerically coded, illustrated in Table 3.9.

Table 3.9. Numerical coding for development of gender regression model

Variable	Coding
Gender	0 = Male, and 1 = Female
Traffic flow regime	0 = overnight flow, 1 = day flow, 2 = morning peak flow, 3 = evening peak flow
Lighting condition	0 = Daylight, and 1 = Darkness
Weather	0 = Fine, and 1 = Wet
Road surface condition	0 = Dry, and 1 = Wet

3.8. Model development for environmental conditions

The analytic methodology for modelling the varied environmental conditions is illustrated in Table 3.10. Firstly, statistical analysis of the crashes is undertaken, followed by the generation of the heat maps. This results in crash rates and investigates the risk's spatial variation for varied environmental conditions with different infrastructure. Three deep learning models are constructed with the input variables of spatial, personal and infrastructure variables, described in Table 3.11. The output variables of each model are described in Table 3.12. A similar network structure is employed.

Table 3.10. Analytic methodology used for modelling the varied environmental conditions

Step	Variable modelled	Output modelled
Traditional safety model	a) Crash frequency	a) Crash Percentage
Heat maps	a) WGS84 coordinates of each crash	a) Heatmaps
Deep learning neural network	Input variables of a) Spatial b) Personal c) Infrastructure	Predictive riskiest age group, evaluated through: e) ROC curves f) AUROC values g) Gain chart h) Lift chart
Variable importance	a) Importance b) Chi-square statistic c) Cramer V	a) Normalised importance (% age) b) Statistical association c) Degree of association
Logistic regression: 1	a) Hourly flow rate b) Traffic flow regime c) Peak d) Rider gender e) Lighting	a) Regression equation b) Odds ratio.
Logistic regression: 2	a) Hourly flow rate b) Traffic flow regime c) Peak d) Rider gender e) Meteorology	a) Regression equation b) Odds ratio.

Table 3.11. Input variable for the three proposed predictive environment models

No.	Input Variable	Values
1.	**Spatial**	
1.1	Journey hour (hour in which the crash has occurred)	0-23.
1.2	Number of vehicles (number of vehicles involved in the crash).	1-5.
1.3	Month of Journey (month in which the crash has occurred).	Jan-Dec.
1.4	Journey Day (day of the week on which crash has occurred. The day, month and hour of the journey are a representation of the traffic flow regime that was plying at the time of the crash)	Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday.
1.5	Journey weekday/ weekend	Weekday. Weekend.
2.	**Personal**	
2.1	Gender (rider gender).	Male, Female, and Unknown
2.2	Age (rider age)	0-17, 18-24,25-34, 35-44, 45-54,55-64, and over 65.
2.3	Age and Gender (combined)	0-17 male, 14-24 male,25-34 male, 35-44 male, 45-54 male,55-64 male, over 65 male, 0-17 female, 14-24 female,25-34 female, 35-44 female, 45-54 female,55-64 female, and over 65 females.
2.4	Journey purpose (purpose of the journey being undertaken in which the crash has occurred).	Commuting, work trip, School Journey by Pupil, taking pupil to school, other, Unknown.
3.	**Infrastructure**	
3.1.	Road type (type of road infrastructure present at the crash spot).	Dual Carriageway, One-way street, Roundabout, single carriageway, slip road,
3.2.	Speed limit (maximum permissible speed limit on the road).	20-70

3.3.	1st Road class	Functional classification of the roadway into: A, B, C, E, U
3.4.	Road hierarchy level (difference in the functional classification of 1st and 2nd road class)	0-4
3.5.	Road hierarchy level and direction (difference in the functional classification of 1st and 2nd road class including the direction of change)	-4 to 4
3.6.	Junction detail (intersection type).	Crossroad, Mini Roundabout, Multiple Junction, Straight Road, Roundabout, Slip Road, T or Staggered, Private Drive
3.7.	Junction control (type of control that is employed at the intersection).	No Control, Traffic Signal, Give way or uncontrolled, Stop sign
3.8.	2nd Road class.	Functional classification of the roadway into: A, B, C, E, U
3.9.	Vehicle manoeuvre (The manoeuvre that the rider was performing/intending to perform when the crash occurred).	Changing lanes, Going ahead, Moving off, Overtaking, Parked, Reversing, Slowing/stopping, Turning, U-turn, Waiting to go ahead, waiting to turn
3.10.	Vehicle junction location (location of the cyclist to the junction when the crash has occurred).	Approaching junction or waiting/parked at junction exit, cleared junction or waiting/parked at junction exit, Entering, Leaving, Mid Junction, Straight Road (Not at or within 20 meters of the junction)
3.11	Road location of vehicle (location of the cyclist to the road infrastructure, when the crash has occurred).	Bus Lane, Busway, Cycle lane, cycleway, footpath, on layby or hard shoulder, main carriageway, tram/light rail track
3.12.	Carriageway hazard (additional unexpected hazards on the carriageway).	Animal in the carriageway (except ridden horse), Dislodged vehicle load in carriageway, Dislodged vehicle load in carriageway, Other object in carriageway, and none

Table 3.12. Predicted risky environmental conditions (light and meteorological Road Surface Condition)

Output Variable: Riskiest Environmental condition of	
Darkness - No street lighting, and dry	Darkness - Street lights present, unlit and dry
Darkness - No street lighting, and wet/damp	Darkness - Street lights present, unlit and wet/damp
Darkness - Street lighting unknown, and dry	Daylight and dry
Darkness - Street lighting unknown, and wet/damp	Daylight and frost
Darkness - Street lights present, lit and dry	Daylight and snow
Darkness - Street lights present, lit and snow	Daylight and wet/damp
Darkness - Street lights present, lit and wet/damp	n/a

As both the environment variables of meteorology and lighting conditions are ordinal variables, two logistic regression models are constructed. The input variables of hourly flow rate, traffic flow regime, peak, rider gender, and lighting/ meteorology are codded similar to presented in section 3.7.3.

3.9. Model development for micro-infrastructure variables

The final modelling is performed to model the micro-infrastructure parameters affecting the cyclist safety. This modeling is performed by considering the knowledge acquired from earlier modelling of age, gender and environment conditions. The step-by-step methodology applied is illustrated in Fig 3.6.

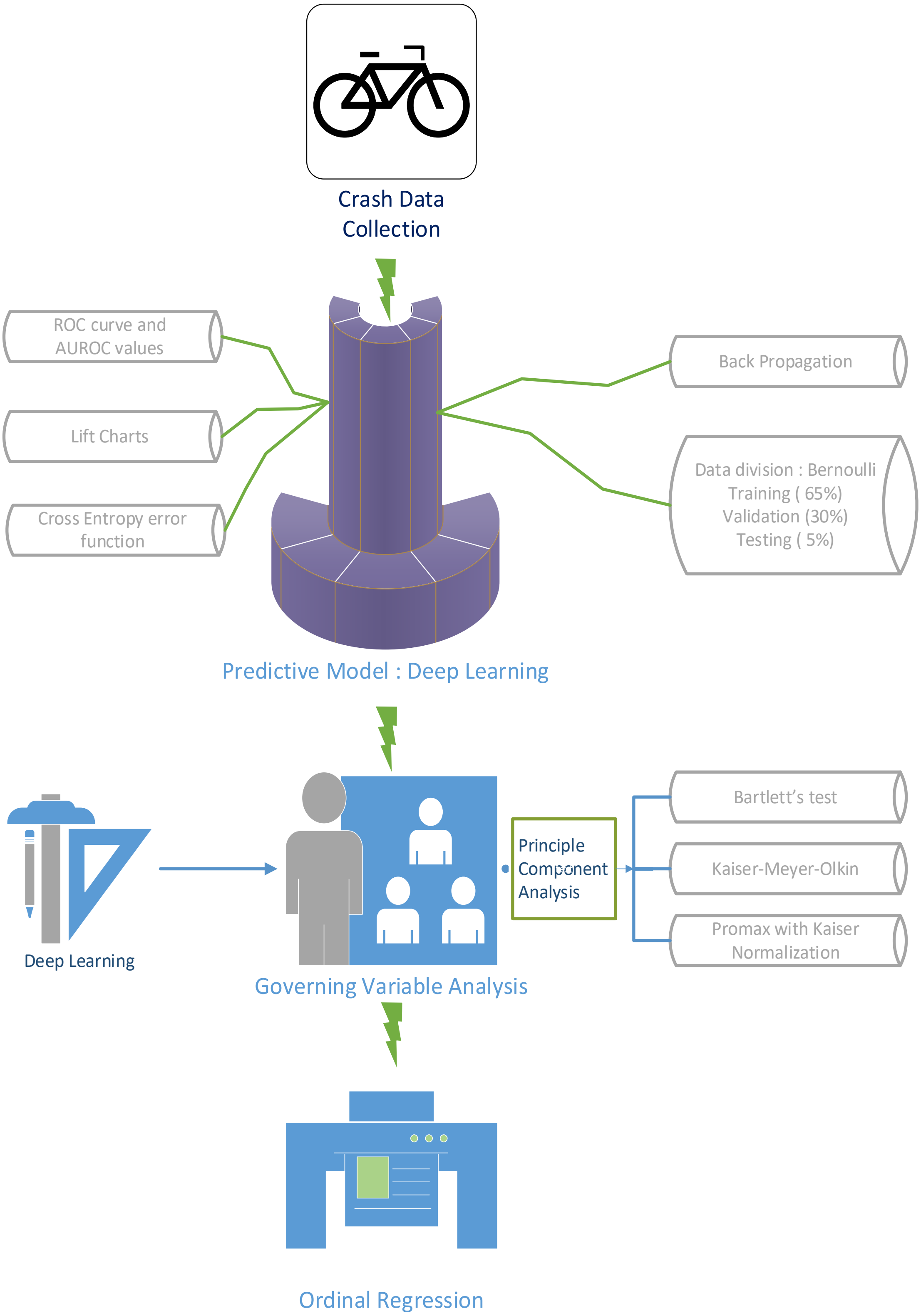


Figure 3.6. Methodological framework for modelling the micro-infrastructure variable

3.9.1. Deep learning neural model

Four predictive deep learning infrastructure models are constructed using same deep learning, neural network classifier, backpropagation, cross-entropy error function, and scaled conjugate gradient optimisation. The same four-step learning iterative procedure is used, as demonstrated in section 3.6.2. However, as fewer input variables are used, a less complicated network is used, with fewer units in the hidden layers. Through the literature review, the critical variables affecting the safe micro-infrastructure variables are identified. These are complemented by the critical varia-

Table 3.13. Input variable of different infrastructure models

	Model 1	Model 2	Model 3	Model 4
Input variables	Month	Month	Month	Month
	Day	Day	Day	Day
	Hour	Hour	Hour	Hour
	Road Hierarchy level and direction	Road Hierarchy level and direction	Road Hierarchy level and direction	Road Hierarchy level and direction
	Age and Gender	Age and Gender	Age and Gender	Age and Gender
	Environment Light Road surface condition	Environment Light Road surface condition	Environment Light Road surface condition	Environment Light Road surface condition
		Road Type	*Road Type*	*Road Type*
			Junction Detail and Control	*Vehicle Manoeuvre*
Output	*Road Type*	*Junction Detail and Control*	*Vehicle Manoeuvre*	*Junction Location of Vehicle*

-bles identified in the variable importance model in Chapter 5, 6, and 7. These are used as input variables in the data learning model. In the first model, the input variables of: a) Traffic flow regime; represented by month, day and hour of journey, b) Sudden change in the functional road hierarchy, c) Personal attribute of age and gender, and d) Environmental conditions of lighting and meteorological road surface conditions. Each model's input variables are tabulated in Table 3.13.

The output of model one defines the riskiest road type, predicted through the combination of input variables. The second model predicts the riskiest type of roadway intersection and the type of control employed. Through the initial input variables, road type (output from Model 1), and junction type and control (output from Model 2), the riskiest vehicle manoeuvre is predicted in Model 3. Similarly, the riskiest location within the intersection is predicted in Model 4, considering the initial input variables, road type (output from model 1), and vehicle manoeuvre (output from model 1). Each models' output value are presented in Table 3.14. The primary motivation for predicting the micro infrastructure parameters is to develop an in-depth understanding of the mechanism of interaction of cyclists with the infrastructure and develop a corresponding predictive model.

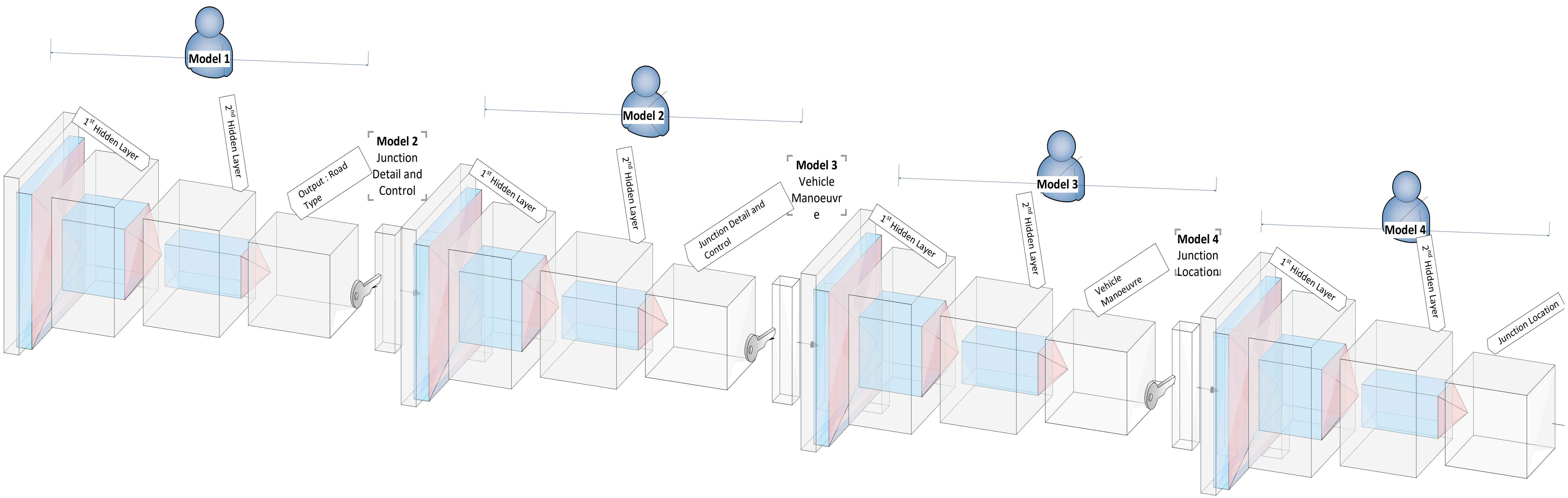


Figure 3.7. Schematic modelling of four micro-infrastructure models

Table 3.14. Riskiest output variables for each infrastructure variable model

Model 1	Model 2	Model 3	Model 4
Dual Carriageway	Crossroads with Automatic traffic signal	Changing lane to the right/left	Approaching junction or waiting/parked at junction exit
One way street	Crossroads with Give way or uncontrolled	Going ahead left-hand bend	Cleared junction or waiting/parked at junction exit
Roundabout	Crossroads with Stop sign	Going ahead other	Entering from slip road
Single Carriageway	Mini roundabout with Give way or uncontrolled	Going ahead right-hand bend	Entering main road
Slip Road	Multiple Junction with Automatic traffic signal	Moving off	Entering roundabout
	Multiple Junction with Give way or uncontrolled	Overtaking moving vehicle on its offside	Leaving main road
	Other junction with Automatic traffic signal	Overtaking on nearside	Leaving roundabout
	Other junction with Give way or uncontrolled	Overtaking stationary vehicle on its offside	Mid junction - on roundabout or on main road
	Other junction with Stop sign	Parked	
	Roundabout with Automatic traffic signal	Reversing	
	Roundabout with Give way or uncontrolled	Slowing or stopping	
	Slip Road with Give way or uncontrolled	Turning left	
	T or staggered junction with Automatic traffic signal	Turning right	

	T or staggered junction with Give way or uncontrolled	U turn	
	T or staggered junction with No Control	Waiting to go ahead but held up	
	T or staggered junction with Stop sign	Waiting to turn left	
	Using private drive with Give way or uncontrolled	Waiting to turn right	

The less complicated network is illustrated in Table 3.15.

Table 3.15. The network structure of the four infrastructure predictive model

Network Information					
Model No.		1	2	3	4
Input Layer	Number of Units	79	83	100	109
Hidden Layer(s)	Number of Hidden Layers	2	2	2	2
	Number of Units in Hidden Layer 1	35	35	35	35
	Number of Units in Hidden Layer 2	35	35	35	35
	Activation Function: Hyperbolic tangent				
Output Layer	Dependent Variables	Road Type	Junction Detail and Control	Vehicle Manoeuvre	Junction Location of Vehicle
	Number of Units	6	17	18	8
	Activation Function: SoftMax				
Error Function	Cross Entropy Error	637.6	661.1	528.5	764.0
Training	Type				Batch

	Optimisation	Scaled conjugate gradient
	Initial lambda, and sigma	10^{-7}
	Initial offset	$\pm 10^{-7}$
	Initial Centre	0
Stopping and Memory Criterion	Maximum iterations without an error change	99,999
	Maximum training epochs	99,999
	Minimum change in the training error (relative)	10^{-5}
	Minimum change in the training error ratio (relative)	10^{-5}

3.9.2. Governing variable analysis

Firstly, the importance of each variable in the data-learning model is identified through variable importance. This is measured by measuring how the predicted output value changes viz a viz change in the input variable, followed by calculating each variable's normalised importance concerning the most critical governing variable, expressed as percentages. The second approach involves using exploratory data analysis, i.e., Principal Component Analysis (PCA). The input variables are grouped, and the number of groups is determined through the eigenvalue curve. The component groups having eigenvalues more significant than one are selected, as these can account for a larger share of variance in the variables. A correlation matrix is then developed to check the association within the variables, and variables correlated at a 95% confidence interval are used for further analysis. The crashes are a multi-factor phenomenon, and the input variables are assumed correlated (tested by KMO); therefore, this prompted the use of the oblique rotation of Promax with Kaiser

Normalization. The rotation maximises each variable's loading on one of the extracted factors whilst minimising the loading on all other factors.

3.10. Chapter summary

This chapter has presented the methodological framework, appropriate research methods, method of data collection and explained each stage of the research aimed at addressing the research questions. The study is divided into six stages: a review of literature, investigating study area, age modelling, gender, environmental conditions, and micro-infrastructure modelling. Each stage is divided into several steps, modelled through an appropriate identified research method. These include descriptive analysis, deep learning, chi-square test, principal component analysis, Levene test, and different regression techniques. After the requisite analysis is successfully performed, the process and outcomes are presented in the following chapters.

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Chapter 4.

Study Area: Tyne and Wear, UK

The Tyne and Wear County in the northeast of England is selected as the area of investigation. It comprises a core urban area covering the Tyneside and Wearside conurbations, surrounded by several rural areas. This is one of the nine official regions of England, having a population of 1.13 million, encompassing 3,317 sq. miles, and an estimated 693,000 jobs. It houses five boroughs (Fig 4.1); Gateshead, Newcastle-upon-Tyne, North Tyneside, South Tyneside, and Sunderland, with thirteen urban and three rural districts. The study area has a strong local identity and a rich heritage, particularly concerning innovations in transport. One of the significant challenges presently faced by the area is meeting the carbon reduction targets and tackling the high levels of deprivation and poor health in some areas.

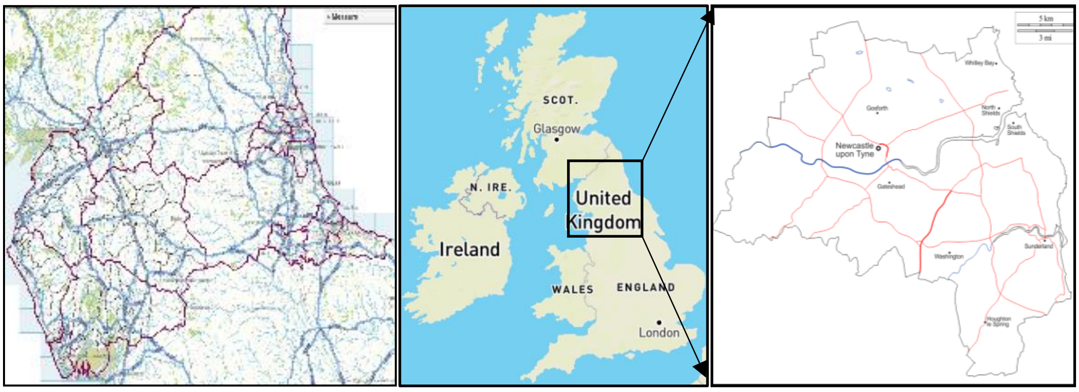


Figure 4.1. Location and Boundaries of the study area

In this chapter, firstly, understanding of how the cyclist usage varies with the month, hour and day of the journey is presented in section 4.1. The cyclist flow variation concerning changing lighting conditions in 4.2 and changing meteorological conditions in 4.3. The usage variation concerning the personal attribute of age and gender is presented in 4.4. The temporal and spatial variation of cyclist crashes is presented in 4.5, followed by the infrastructure variation of crashes in 4.6, and chapter summary in 4.7

4.1. Traffic Flow

4.1.1. Variation of traffic flow with the month of journey

The variation of the traffic flow with the month of the year is presented in Table 4.1. The average flow per month is 297,902, with a median of 285,066, a minimum flow of 143,601 in December, and a maximum of 445,727 cyclists in July. The traffic flow starts increasing from May, with the peak occurring from June to August. Afterwards, the flow decreases continuously, with the lowest flow in December. The flow and flow rate variation with the month is plotted in Fig 4.2 and Fig 4.3, respectively. It can be interpreted that the month of the journey directly affects the cyclist's flow. It is essential to understand that this is a spurious relation, with the lurking variable (confounder) being the lighting conditions, precipitation, and the journey purpose. The purpose of the journey significantly varies with the month of the journey in the United Kingdom, e.g., the month of December is correlated with the Christmas holidays.

Table 4.1. Variation of the traffic flow with the month

Month	F_L	F_{LR}	Flow type
January	148555	4.4	non-Peak

February	207098	5.8	non-Peak
March	252427	7.1	non-Peak
April	241248	6.7	non-Peak
May	317704	8.9	Inter-Peak
June	444326	12.4	Peak
July	445727	12.5	Peak
August	391025	10.9	Peak
September	366170	10.2	Inter-Peak
October	358555	10.0	Inter-Peak
November	249949	7.0	non-Peak
December	143601	4.0	non-Peak
Total	3574826	100	n/a
Mean	297902	n/a	n/a
Median	285066	n/a	n/a

where F_L = Flow, and F_{LR} = Flow rate

Figure 4.2. Variation of the traffic flow with the month

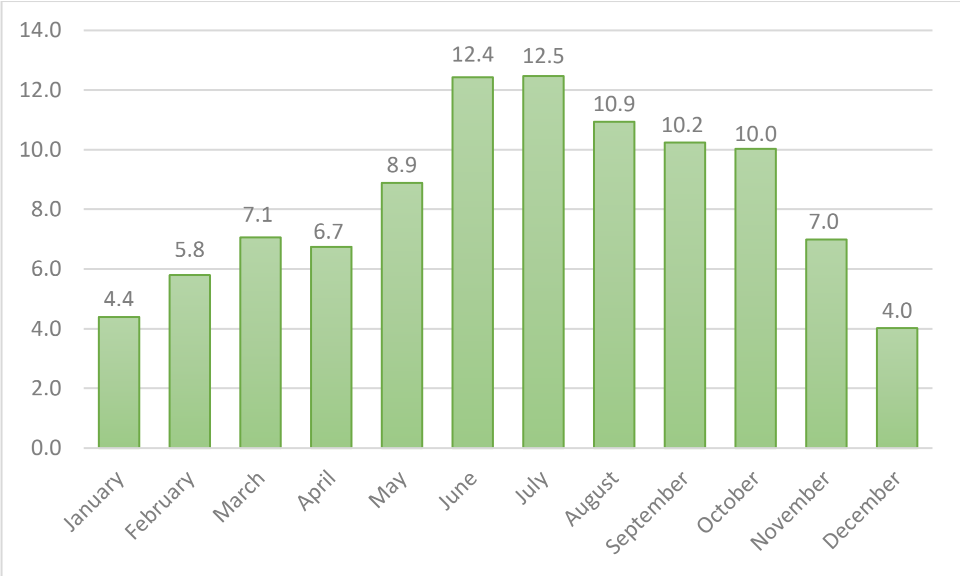


Figure 4.3. Variation of the traffic flow rate with the month

4.1.2. Variation of the traffic flow with the hour of journey

The hourly variation of the traffic flow is presented in Table 4.2. The average flow per hour is 148,951 (408), a median of 173,129 (474), a maximum of 330,432 (905) for 17:00-18:00, and a minimum of 13,219 (36) cyclist per year (per day) for 03:00-04:00 hours. The daily average flow is 9,794 cyclists per day. The hourly distribution results indicate that the cyclists flow increases as expected with the morning hours, with the morning peak from 07:00 – 10:00 hours. This is followed by a slight decrease in the traffic flow, i.e. inter-peak from 10:00 to 15:00, and evening peak from 15:00 to 18:00, followed by an inter-peak hour and a non-peak traffic flow regime from 19:00 to 7:00 hours. Interestingly, the evening peak is higher and longer than the morning peak, which leads to infer that the flow builds up during the day and a more sudden incoming trips to complete the journey with the working hour closure. A minimal cycling flow (5%) occurs from 22:00 to 5:00 hours.

The hourly variation of the flow, morning and evening flow are plotted in Fig. 4.4, Fig. 4.5, and Fig. 4.6, respectively. It can be inferred that the traffic flow and the journey hour are correlated with each other. This is an expected result, as demand to travel is derived by the working hours, commuter times, opening and closing time of leisure, shopping, and others.

Table 4.2. Hourly variation of traffic flow

Journey Hour	F_{LY}	F_{LAH}	F_R	Flow type
1	22128	60.6	0.62	Non-Peak
2	18090	49.6	0.51	Non-Peak
3	13376	36.6	0.37	Non-Peak
4	13219	36.2	0.37	Non-Peak
5	17935	49.1	0.50	Non-Peak
6	46914	128.5	1.31	Non-Peak
7	125878	344.9	3.52	Non-Peak
8	221054	605.4	6.18	Morning Peak
9	285898	783.3	8.00	Morning Peak
10	213058	583.7	5.96	Morning Peak
11	198577	544.0	5.55	Inter-Peak
12	205888	564.1	5.76	Inter-Peak
13	215531	590.5	6.03	Inter-Peak
14	219224	600.6	6.13	Inter-Peak
15	228030	624.7	6.38	Inter-Peak
16	254738	697.9	7.13	Evening Peak
17	295327	809.1	8.26	Evening Peak
18	330432	905.3	9.24	Evening Peak
19	225189	617.0	6.30	Inter-Peak
20	147682	404.6	4.13	Non-Peak

21	103008	282.2	2.88	Non-Peak
22	73809	202.2	2.06	Non-Peak
23	57140	156.5	1.60	Non-Peak
24	42701	117.0	1.19	Non-Peak
Mean	148951	408	n/a	n/a
Median	173129	474	n/a	n/a

where F_L = Flow, and F_{LR} = Flow rate, F_{LY} =Flow per year, and F_{LAH} = Average flow per hour

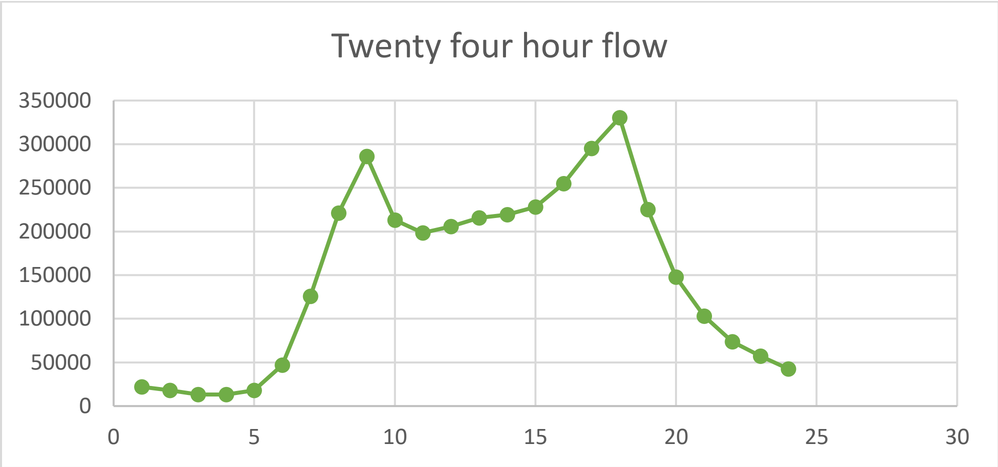


Figure 4.4. Variation of the traffic flow with the hour of journey

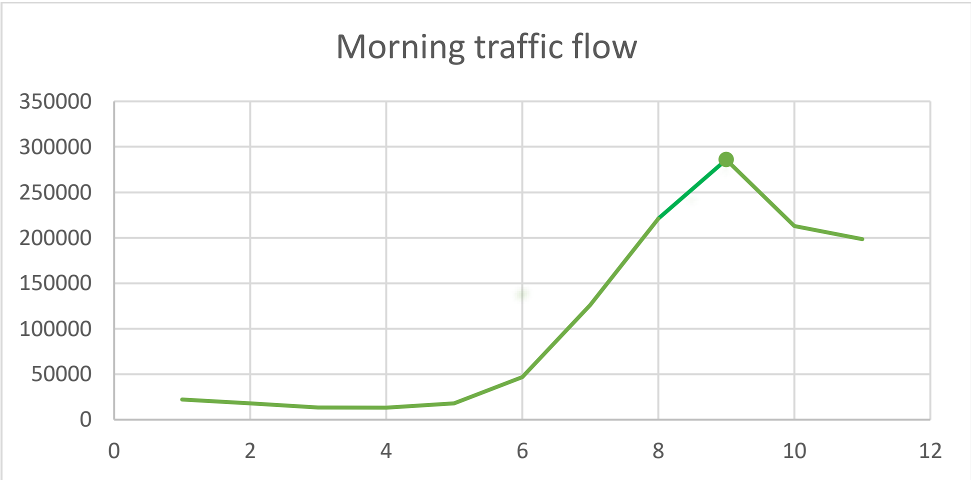


Figure 4.5. Variation of the morning traffic flow

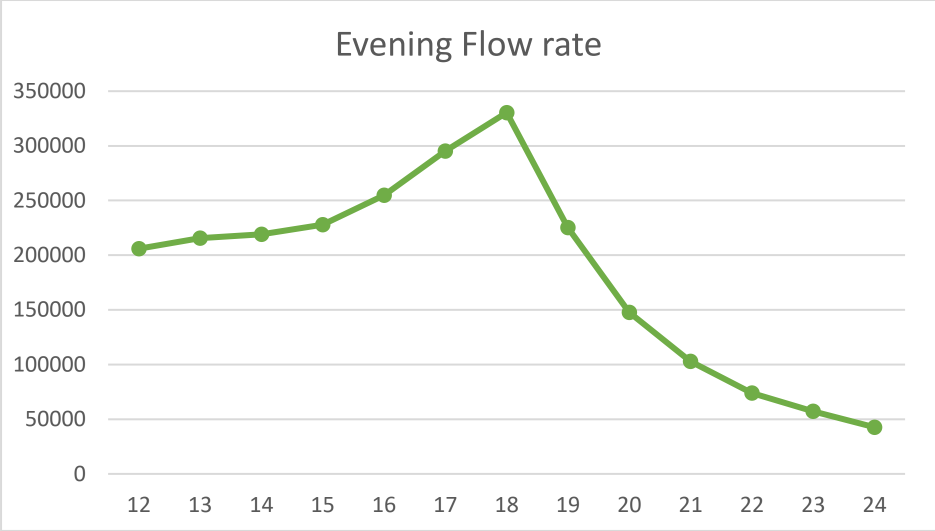


Figure 4.6. Variation of the evening traffic flow

4.1.3. Daily variation of the traffic flow

The daily variation of the traffic flow is presented in Table 4.3, and the flow rate variation in Fig. 4.7. It can be concluded that the weekday flow is significantly higher than the weekend flow, with the highest flow on Tuesday 587,629, a minimum of 369,872 on Sunday, an average of 510, 689, and a median of 564, 244 cyclists per year. The peak flow occurs on Tuesday, with a slight decrease up to Friday and a sudden drop of 50% for the weekend. Although weekend flow is low, it is still considerable, which leads to infer that there are some non-commuter trips for leisure, shopping, and other things. Hence, the journey purpose is significantly varied for the study area.

Table 4.3. Daily variation of the traffic flow

Day	F_L	F_{LR}
Monday	564244	15.8
Tuesday	587629	16.4
Wednesday	579442	16.2

Thursday	565721	15.8
Friday	536798	15.0
Saturday	371120	10.4
Sunday	369872	10.3
Total	3574826	100
Mean	510689	n/a
Median	564244	n/a

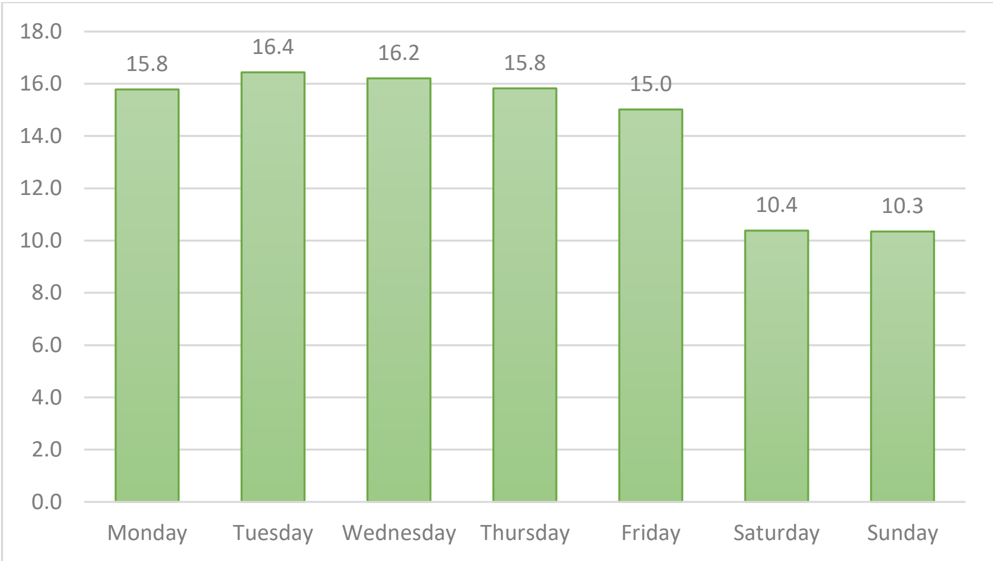


Figure 4.7. Daily variation of the flow rate

4.2. Variation of lighting conditions

The monthly variation of lighting hours is presented in Table. 4.4 and Fig. 4.8. The lighting hours increase from January to June and then decreases up to December. This variation is quite significant, with 2.4 times higher lighting hours in June than in December. This is peculiar to the meteorology of northeast England. The road users choose to travel based upon experiences from previous years, especially the cyclists, who are found to alter their choices concerning their selection of mode of travel (Heinen, Maat and van Wee, 2011).

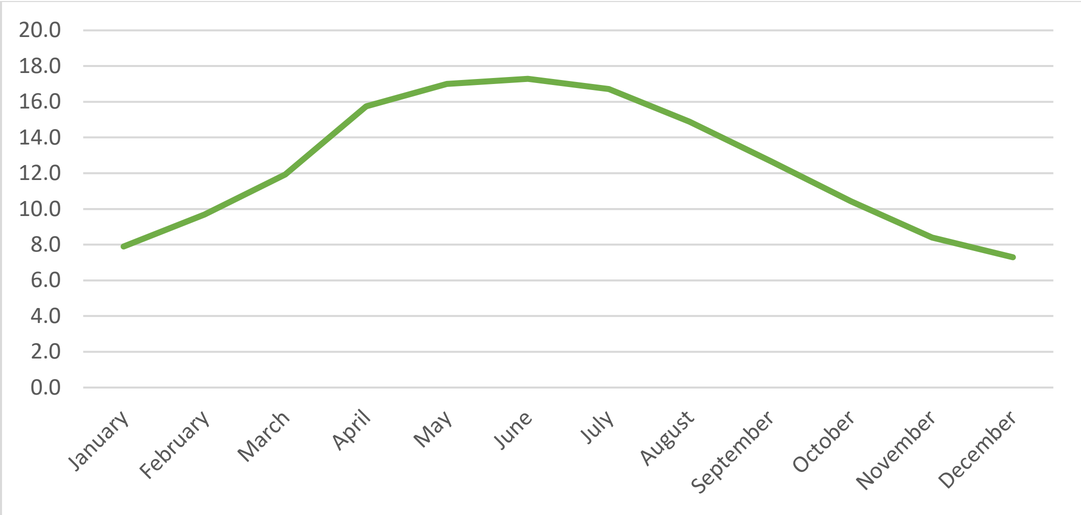


Figure 4.8. Monthly variation of daylight hours

Table 4.4. Monthly variation of daylight hours

Month	Daylight Hours
January	7.9
February	9.7
March	11.9
April	15.8
May	17.0
June	17.3
July	16.7
August	14.9
September	12.7
October	10.4
November	8.4
December	7.3

The monthly variation of traffic flow with the daylight hours is presented in Table 4.5. Furthermore, the traffic flow variation during different lighting conditions is evaluated by comparing the traffic flow for each day with the lighting hours for that day (attached in Appendices). The final analysis is presented in Table 4.6, wherein it is found that 81% of the traffic flow occurs during daylight and only 19% during darkness.

Table 4.5. Variation of the flow with the change in Lighting hours

Daylight hours	F_L
7.3	143601
7.9	148555
8.4	249949
9.7	207098
10.4	358555
11.9	252427
12.7	366170
14.9	391025
15.8	241248
16.7	445727
17	317704
17.3	444326

Table 4.6. Variation of the flow rate with the lighting hours

Lighting condition	F_L	F_{LR}
Daylight	2912237	81.47
Darkness	662589	18.53
Total	3574826	n/a

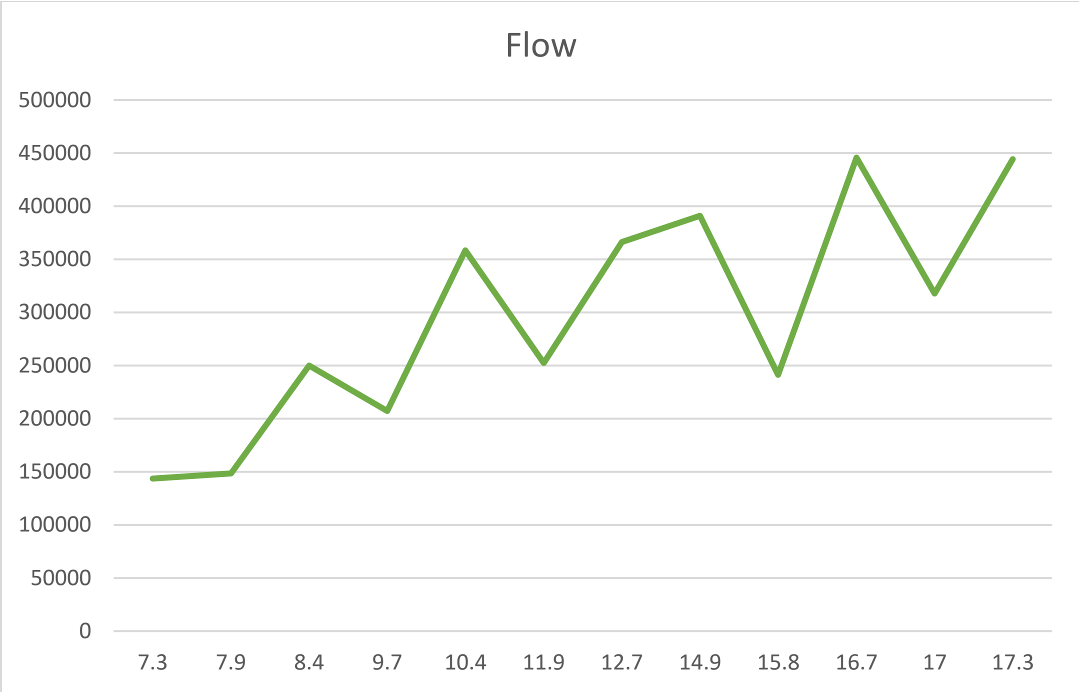


Figure 4.9. Flow variation with the change in the daylight hours.

4.3. Variation of meteorological conditions

The meteorological condition directly impacts the road surface condition. Both these variables are sometimes used synonymously, as there exists a cause effect relationship between the two variables. However, there are certain conditions during which the two variables may be different, such as after a heavy precipitation, the meteorological condition maybe classified as fine, however the road surface condition may still be wet. Similarly at the start of a drizzle, the meteorological condition maybe classified as wet, however, the road surface condition can still be wet. Hence, the two variables need to be modelled separately, but still have a cause-effect relationship between the them. The meteorological variation with the month of the journey is presented in Table 4.7 and Fig. 4.10. The average precipitation is 462 mm, median 389 mm, a minimum of 109 mm, and a maximum of 1090 mm per month. There is an irregular rainfall pattern which initially increases sharply in the spring (2.5 times compared with January) March-April with the peak in April, and a sudden dip in May to only 109 mm, which then rises smoothly up to August to 548 mm, and then finally decreases to 217mm in December.

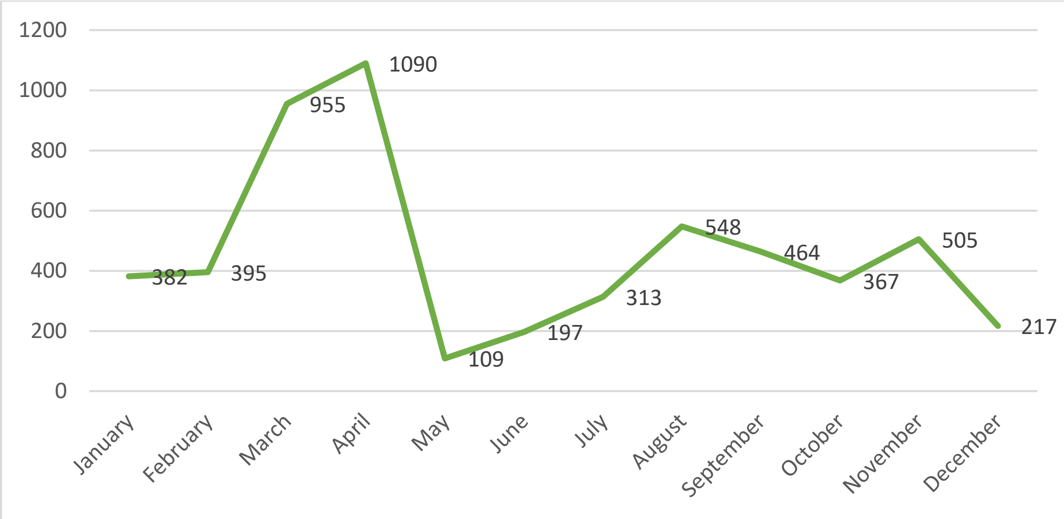


Figure 4.10. Variation of precipitation in mm with the month of journey

Table 4.7. Meteorological variation with the month of the journey

Month	Precipitation in mm
January	382.0
February	395.1
March	954.9
April	1089.8
May	108.6
June	196.5
July	313.3
August	548.0
September	463.7
October	367.2
November	504.6
December	216.6
Total	5540.2

Mean	461.7
Median	388.6

The cyclist mode choice is highly varied, depending upon the meteorology, lighting conditions, and season (temperature). The cyclists are reported to change their mode choice on a daily bases due to a change in these conditions. The cyclists cannot be considered uniform; they are composed of riders with different skills, experience, part and full-time cyclists. The same heterogeneity is observed in their mode selection. Although the month of the journey is not a variable that should itself affect the mode usage. However, this is a hoax variable that can be used effectively and efficiently for modelling due to a high correlation. The underlying causation and correlations need to be identified to improve modelling. Such modelling will help understand the nanoscopic location-specific area problems and develop recommendation measures to improve the mode's safety and attractiveness. This is essential to achieve the pathway towards a green transportation system. With the change in the environmental conditions, the frequency of other sustainable modes, such as public transport, can be increased. Even discounted fares can also be provided for public transport or car-share during these adverse environmental conditions to a cyclist. This can leads to an integrated sustainable transportation system, which focuses on providing mobility as a service. However, before any such initiative or planning is undertaken, an in-depth understanding of these adverse conditions and their combined effect to affect the safe usage of particular cyclist infrastructure needs to be modelled.

4.4. Bicycle usage by age and gender

The bicycle usage by age and gender in terms of number of trips per person is tabulated in Table 4.8, and by miles traversed in Table 4.9. The average number of cyclist trips performed per person is 16.6 per year, with a male average of 25.4 and a female average of 7.9. The overall trips per age groups continuously increase from 0- 49, and then decrease after that, with the maximum trip rate for the 40-49 age group (22.5), and least for the 70+ age group (6.1). A similar pattern is observed across gender; however, young females, i.e. 0-16 (7.5), perform a greater number of trips than their immediate corresponding group of 17-20 (2.0). The number of trips carried out by different gender is significantly different, with males making thrice the number of trips than females. This variation varies with the age groups, ranging from 1.7 to 9.7 times, and a mean of 3.2.

Table 4.8. Number of cycle trip made per person in the study area

Age group	Overall		Males		Female		T_{MF}
	T_P	T_R	T_P	T_R	T_P	T_R	
0-16	12.5	9.4	17.3	8.5	7.5	11.8	1.7
17-20	19.3	14.6	35.8	17.6	2.0	3.1	9.7
21-29	19.5	14.6	26.2	12.9	12.6	20.0	1.5
30-39	21.7	16.3	30.8	15.2	12.7	20.1	1.7
40-49	22.5	16.9	34.1	16.8	11.1	17.5	2.0
50-59	18.5	13.9	27.5	13.5	9.7	15.3	1.9
60-69	12.9	9.7	20.1	9.9	6.1	9.6	2.1
70+	6.1	4.6	11.4	5.6	1.6	2.5	3.8
Total	132.9	100.0	203.3	100.0	63.2	100.0	3.2
Average	16.6	n/a	25.4	n/a	7.9	n/a	n/a

where T_P = Trips per person, T_R = Trips rate, and T_{MF} = Male/Female ratio of trips per person

The average distance traversed per person in a year is 57.25 miles; male ride 92.3, whereas females ride 12.5 miles per year. A similar pattern is observed in the distance travelled, with 40-49 age groups (85.5 miles per year) riding the longest distance and greater than 70 age groups (17.2 miles per year) riding the shortest. The distance traversed continuously increase from 0- 49 and then decreases. The gender difference is quite significant, with males travelling four times higher distance than women. The variation within the age groups ranges between 1.4 to 40.1 times, mean and median of 4.1. Hence, we can conclude that both the number of trip and miles traversed are significantly different for riders belonging to different age and gender groups.

Table 4.9. Total mile traversed per person in the study area

Age group	Overall		Males		Female		M_{MF}
	M_P	M_R	M_P	M_R	M_P	M_R	
0-16	21.3	4.6	30.4	4.1	11.7	6.5	2.6
17-20	67.5	14.7	128.3	17.4	3.2	1.8	40.1
21-29	55.6	12.1	65.4	8.9	45.7	25.3	1.4
30-39	82.6	18.0	132.4	17.9	33.9	18.8	3.9
40-49	85.5	18.7	146.0	19.8	26.3	14.6	5.6
50-59	84.1	18.4	130.7	17.7	38.8	21.4	3.4
60-69	44.2	9.7	72.9	9.9	17.0	9.4	4.3
70+	17.2	3.8	32.6	4.4	4.3	2.4	7.6
Total	458.0	100	738.9	100	180.9	100.0	4.1
Average	57.25	n/a	92.4	n/a	22.6	n/a	n/a

where M_P = Miles per person, M_R = Miles rate, and M_{MF} = Male/Female ratio of miles per person

4.5. Temporal and Spatial variation of crashes

There are 3,325 bicyclist crashes reported in the study area between 2005 and 2018. Out of these, 79.3% are slight, 19.9% are serious, and 0.8% are fatal.

Table 4.10. Crash recorded in north-east England from 2005-2018

Time Period	2005-2018
Slight	2638
Serious	661
Fatal	26
Total Number of crashes	3325

4.5.1. Hourly variation of crashes

The crash distribution of the journey hour is presented in Table 4.11. The crash rate is highly varied with the hour of the journey. The crashes start increasing from 7:00 am, morning peak occurs between 8:00 am and 9:00 am, with 7.8% of crashes. The rate starts decreasing thereafter, followed by a significant surge in the evening crash rate from 15:00. The evening peak occurs between 17:00-18:00, with 13.3% of crashes occurring during this hour. After 20:00, the crash rate starts decreasing.

Table 4.11. Hourly crash rate

Journey hour	f	C_R
1	24	0.7
2	7	0.2
3	4	0.1

4	7	0.2
5	4	0.1
6	13	0.4
7	38	1.1
8	113	3.4
9	260	7.8
10	103	3.1
11	112	3.4
12	152	4.6
13	169	5.1
14	193	5.8
15	175	5.3
16	294	8.8
17	405	12.2
18	444	13.4
19	282	8.5
20	206	6.2
21	111	3.3
22	99	3.0
23	79	2.4
24	31	0.9
Total	3325	100

where f = Frequency, and C_R = Crash rate

4.5.2. Daily variation of crashes

The daily variation of the crashes is presented in Table 4.12, and the weekday/weekend variation in Table 4.13. The crash variation is not significantly different for the weekdays, with a lower crash rate on Tuesday. The crashes on weekdays are significantly higher compared to weekends. The highest crash rate occurs on Thursday with a 15.8% crash rate and the minimum on Sunday with a 10.8% crash rate. Around 24% of the crashes occur on weekends.

Table 4.12. Daily variation of crashes

Day of the week	*f*	C_R
Monday	516	15.5
Tuesday	466	14.0
Wednesday	516	15.5
Thursday	525	15.8
Friday	520	15.6
Saturday	442	13.3
Sunday	340	10.2
Total	3325	100

Table 4.13. Weekday/Weekend crash rate

Day	*f*	C_R
Weekday	2543	76.5
Weekend	782	23.5
Total	3325	100.00

4.5.3. Monthly crash variation

The monthly variation of crashes is presented in Table 4.14. The number of crashes increase from January to July and then decrease up to December. However, the only outlier is April month, which has a higher crash rate than May. The similar variation is observed in the monthly precipitation for these two months (Section 4.3). The mean and median crashes per month are 277, with the maximum crash rate in July as 13.4% and the minimum reported in December as 3.1%. Overall, crashes are high from June to September.

Table 4.14. Monthly crash rate

Month	*f*	C_R	Month	*f*	C_R	
January	148	4.5	July	445	13.4	
February	211	6.3	August	400	12.0	
March	219	6.6	September	370	11.1	
April	289	8.7	October	275	8.3	
May	280	8.4	November	222	6.7	
June	363	10.9	December	103	3.1	
Total	3325	100.0	Mean	277.1	Median	277.5

4.5.4. Crash variation for different environment conditions

The variation of crashes with the lighting conditions is tabulated in Table 4.15, and meteorological conditions in Table 4.16, and meteorological road surface condition in Table 4.17. Most crashes (83.3%) occur during daylight, and for the crashes occurring in darkness, 88% have streetlight present and lit. In more than 90% of the cases, the crash occurs in fine weather without high winds, followed by 7% in rainy meteorological conditions. In only 1.8% of crashes, high winds are present. The rain/precipitation may degrade the road environment and leave the road surface wet, affecting the flow conditions through a combination of factors such as loss of friction between the tyre and road surface, the spray of water from other vehicles, and others. Hence, the meteorological road surface condition is also investigated. The road surface is dry in only 82.3% of crashes, contrary to the meteorological conditions, which have dry weather in 92% of crashes.

Table 4.15. Lighting conditions and crash rate

Lighting Conditions	*f*	C_R
Darkness - No Street Lighting	48	1.4
Darkness - Street Lighting Unknown	14	0.4
Darkness - Street Lights present and lit	485	14.6
Darkness - Street Lights present but unlit	9	0.3
Daylight - No Street Lighting	281	8.5
Daylight - Street Lighting Unknown	18	0.5
Daylight - Street Lights Present	2470	74.3
Total	3325	100.0

Table 4.16. Meteorological conditions and crash rate

Meteorological Conditions	*f*	C_R
Fine with high winds	54	1.6
Fine without high winds	3003	90.3
Fog or mist - if hazard	5	0.2
Other	13	0.4
Raining with high winds	8	0.2

Raining without high winds	231	6.9
Snowing with high winds	1	0.0
Snowing without high winds	5	0.2
Unknown	5	0.2
Total	3325	100.0

Table 4.17. Road Surface condition and crash rate

Road Surface condition	*f*	C_R
Dry	2737	82.3
Frost/Ice	17	0.5
Snow	6	0.2
Wet/Damp	565	17.0
Total	3325	100.0

4.5.5. Crash variation with the personal attribute of the rider

The variation of crashes with age and gender of rider are presented in Table 4.18 and Table 4.19. The investigation reveals interesting findings. The crash rate is very high for the young population, with 43% crashes being reported for less than 17 age group. The crash rate decreases with age. Similarly, for gender, 87% of the crashes involve a male rider, whereas only 13% involve female riders.

Table 4.18. Age and crash rate

Age	*f*	C_R
Under 17	1420	42.7
17-24	537	16.2
25-34	494	14.9

35-44	347	10.4
45-54	251	7.5
55-64	115	3.4
Over 64	65	2.0
Unknown	96	2.9
Total	3325	100.0

Table 4.19. Gender and crash rate

Gender	f	C_R
Female	439	13.2
Male	2873	86.4
Not Known	13	0.4
Total	3325	100.0

4.6. Infrastructure variation of crashes

The investigation of infrastructure variation of crashes is essential to understand how different infrastructure variables affect cyclist safety. The crash rates for the following infrastructure variables are investigated:

a) Carriageway type and speed limit,

b) Carriageway location,

c) Number of vehicles,

d) Intersection types and control,

e) Functional road classification,

f) Interaction types and change in hierarchical road level,

g) Intersection location, and

h) Vehicle manoeuvre.

4.6.1. Carriageway and Speed limit

The variation of crashes with the carriageway type is presented in Table 4.20 and variation with the speed limit in Table 4.21. Most crashes occur on a single carriageway (86.2%), which is expected, as cyclists usually prefer this infrastructure type. These are generally quiet streets, with a lower speed limit, and better street infrastructure. For the speed limit, 83% of crashes occur on 30 mph roads. It is widely reported that cyclist prefers such type of infrastructure (see Dublin city cyclist route choice model (Lawson, 2015)), as they have a better-perceived safety, low speed of the interacting vehicles, and ease of movement. Therefore, as the usage is more, there is an expected higher frequency of crashes, e.g. there are no reported crashes on the motorway, as, by law, cyclist is not allowed to use the motorway in the UK.

Table 4.20. Type of Road Infrastructure and crash rate

Carriageway type	f	C_R
Dual Carriageway	141	4.2
One-way street	62	1.9
Roundabout	224	6.7
Single Carriageway	2866	86.2
Slip Road	18	0.5
Unknown	14	0.4
Total	3325	100.0

Table 4.21. Speed limit and crash rate

Speed Limit	*f*	C_R
20.00	96	2.9
30.00	2759	82.9
40.00	156	4.7
50.00	37	1.1
60.00	236	7.1
70.00	41	1.2
Total	3325	100.0

4.6.2. Carriageway location

A cyclist infrastructure is more diverse than motorists in its requirement. There may be special infrastructure provisions provided for cyclists. These include a thoroughly segregated cycleway, shared cycleway with the bus lane, or the rider may be riding on the pavement (footpath). The analysis of the crashes concerning their location on the carriageway is presented in Table 4.22.

Table 4.22. Carriageway location of rider and crash rate

Road Location of the rider	*f*	C_R
Bus Lane	7	0.2
Busway (including guided busway)	113	3.4
Cycle Lane (On main carriageway)	21	0.6
Cycleway or shared use footway	36	1.1
Footway (pavement)	183	5.5
On lay-by or hard shoulder	2	0.1
On the main carriageway - not in restricted lane	2938	88.4
Tram/Light rail track	25	0.8

Total	3325	100.0

The analysis indicates that the majority (>88%) of the crashes occur on the main carriageway, followed by footpath (5.5%), busway (3.4%), and cycleway (1.1%). Hence, the main carriageway elements that have led to the crash need to be evaluated. The corresponding elements of the carriageway that significantly impart the risk need to be identified and modelled.

4.6.3. Number of vehicles involved

The number of vehicles involved in the crash is presented in Table 4.23. The single bicycle crash only accounts for 6.3% of crashes, whereas 93.7% of crashes involve interaction with other vehicles, multiple vehicle account for less than 4%. This leads to conclude that most crashes involve interaction with another vehicle in the study area, contrary to the results reported in high cycling countries such as the Netherlands, where single bicyclist crashes are significant.

Table 4.23. Number of vehicles and crash rate

Number of Vehicles	f	C_R
1.00	211	6.3
2.00	3000	90.2
3.00	100	3.0
4.00	13	0.4
5.00	1	0.0
Total	3325	100.0

4.6.4. Intersections

The crash rate for different intersection types is presented in Table 4.24, and the corresponding control applied in Table 4.25. Although 30% of the crashes occur on the straight section of the road, the most significant number of crashes occur on the T or Staggered type of intersections (45%). This is followed by the roundabouts, where 9.5% of crashes occur, and crossroads, where 9.2% of crashes occur. In terms of intersection control, around 90% of the junction control is the give way or uncontrolled junction; the rest is mostly made up of automatic traffic signal, with a few (0.6%) having stop signal. This may lead to the immediate conclusion that the intersections should be converted into the signalized ones. However, the intersection control type is defined by the traffic flow at the location. If the flow does not demand an automatic signal, employing one can negatively affect the transportation network and impart restlessness or dangerous motorist behaviour. In one example, the Indian Road Congress (IRC-9-1979) has put a maximum restriction of the red phase of only 120 seconds to stop drivers from becoming restless and prevent dangerous driver behaviour. The unnecessary stop and go, created due to automatic control, can impart a higher emission. It is widely reported in vehicular emission modelling that a single harsh acceleration throttle of 5-10 seconds can result in tailpipe emissions as high as that for 300-400 seconds of normal running.

Table 4.24. Type of Intersection and crash rate

Intersection Type	f	C_R
Crossroads	306	9.2
Mini roundabout	31	0.9
Multiple Junction	4	0.1

Not at or within 20 meters	1014	30.5
Other junction	53	1.6
Roundabout	316	9.5
Slip Road	20	0.6
T or staggered junction	1498	45.1
Using private drive or entrance	83	2.5
Total	3325	100.0

The T or staggered junction and give way, or uncontrolled intersections are the lowest type of intersection types and control, provided at the location having lower traffic flow and a low-speed limit. Such a higher proportion of crashes at these locations leads us to infer that the cyclist flow is relatively high in these locations compared with other locations. This reinforces various studies from the literature, which have concluded that the cyclist route choice is highly varied. Instead of the minimum travel path algorithm, they select quite streets with lower traffic flow and speed.

Table 4.25. Type of Intersection control and crash rate

Intersection Controls	*f*	C_R
No control	1016 (1014 straight roads and 2 T junctions)	n/a
Automatic traffic signal	214	9.27
Give way or uncontrolled	2081	90.13
Stop sign	14	0.61
Total	3325	100.00

4.6.5. Functional road classification

An intersection is a roadway facility in which two or more roads either meet or intersect each other. These intersections can have two different road hierarchies of road network that it joins or crosses. The first road class refers to the roadway hierarchical classification on which the vehicle was travelling when the crash occurred. In contrast, the second class is the roadway on which vehicle intended to move (if a crash occurred before exiting intersection) or roadway on which cyclist has come from (if the crash occurred after negotiating the intersection). The functional classification of the roads in the UK (Department for Transport) are

a) M (motorway),
b) A (trunk/ collector roads between cities),
c) B (distributor roads),
d) C (smaller roads intended to connect unclassified roads with A and B road),
e) E (estate road), and
f) U (unclassified).

The crash distribution for the first road class is presented in Table 4.26. The results reveal that Unclassified roads (36.2%) have the highest number of crashes, followed by A roads (25.7%), then B, C and E roads have even share of the crashes. The crash distribution for the second road class is presented in Table 4.27, revealing that the Unclassified road class has 40% of the crashes, increasing from the first road class, thereby implying that the movement towards unclassified road type is a point of concern for the cyclists. From the number of vehicles involved results (section 4.6.3), 94% of the crashes involve a motor vehicle. Hence, we can infer that as the infrastructure moves towards a lower hierarchical road type, the motorist may suddenly change their behaviour. They may decrease the speed to be within the speed limit confines, resulting in sudden braking, affecting how they interact with the cyclist. There are 1022 crashes that do not have a second road class, as these have occurred on the infrastructure other than intersections.

Similarly, for the E road type, there is an increase in the second road class crashes (10.4% first road class, 13.3% for second road class). However, for the higher road classification, there is a decrease in their relative share of crashes. The A road (25.7% for first, 6.2% for second), B (13.3% for first, 3.5% for second), and C (14.4% for first, and 7% for second road type) roads have a lower crash rate compared with the first road class. These findings imply that a cyclist movement from a higher road functional type to a lower functional type is a variable that needs to be modelled in greater depth, requiring a deeper investigation.

Table 4.26. First road class hierarchical classification and crash rate

1st Road Class	*f*	C_R
A	853	25.7
B	443	13.3
C	478	14.4
E	347	10.4
U	1204	36.2
Total	3325	100.0

Table 4.27. Second road class hierarchical classification and crash rate

	f	C_R
A	207	6.2
B	118	3.5

C	232	7.0
E	441	13.3
U	1306	39.3
No second road class	1022	30.7
Total	3325	100.0

4.6.6. Road network Type Interactions

A sudden change in the hierarchical road network can impart dangerous road behaviour, and the road user may immediately need to change their behaviour for negotiating an infrastructure facility safely. Therefore, an investigation of the change in the functional road hierarchy is presented in Table 4.28 and Table 4.29, detailing crash frequencies for different road functional interactions (To the author's knowledge, this is the first time this type of variable is considered for cyclist road safety investigation). The results show that more than 50% of the crashes occur on different road hierarchy levels, with 17% having one level difference, 17% having two, 14% having three and around 4% having a difference in four hierarchical levels. These proportions are quite high, which leads to the postulation that this is a significant variable for the cyclist when traversing an infrastructure, requiring further modelling and deeper understanding.

Table 4.28. Road Hierarchy interactions and crash rate

Type of Road Interactions	*f*	C_R
Straight road	1022	30.74
A-A(M)	7	0.21
A-A	120	3.61

B-A	13	0.39
C-A	19	0.57
Estate-A	15	0.45
U-A	33	0.99
A-B	56	1.68
B-B	28	0.84
C-B	11	0.33
Estate-B	10	0.30
U-B	13	0.39
A-C	100	3.01
B-C	38	1.14
C-C	48	1.44
Estate-C	5	0.15
U-C	41	1.23
A-Estate	68	2.05
B-Estate	55	1.65
C-Estate	77	2.32
Estate-Estate	198	5.95
U-Estate	43	1.29
A-U	229	6.89
B-U	184	5.53
C-U	181	5.44
Estate-U	1	0.03
U-U	710	21.35
Total	3325	100.00

Table 4.29. Functional road hierarchical type and crash rate

Road Hierarchical Type	*f*	C_R
Same Type of Road hierarchy	1104	47.9
The difference in one hierarchical step	391	17.0
The difference in the second hierarchical step	398	17.3
The difference in the third hierarchical step	327	14.2
The difference in four hierarchical steps	83	3.6
Total	2303	

4.6.7. Intersection Location

Table 4.30. Intersection location of vehicle and crash rate

Intersection location of the vehicle	*f*	C_R
Approaching junction or waiting/parked at junction exit	569	24.63
Cleared junction or waiting/parked at junction exit	201	8.70
Entering from the slip road	1	0.04
Entering the main road	476	20.61
Entering roundabout	55	2.38
Leaving the main road	64	2.77
Leaving roundabout	6	0.26
Mid junction - on a roundabout or on the main road	938	40.61

The location within the intersection, which offers highest degree of risk to the cyclist, is also investigated, presented in Table 4.30. It is found that more than 40% of crashes occur mid junctions, followed by approaching the junction or waiting/parked at the exit of the intersection (24.6%) and entering the main road (20.6%), manoeuvre. It is found that more than 80% of crashes either occur mid intersection or approaching the intersection. The uncertain behaviour that the road user must perform while negotiating the intersection can be a significant safety criterion. Such location within the intersection cannot be negated and hence, must be negotiated for traversing the infrastructure. However, as we move towards vehicle and infrastructure automation, vehicle interaction can be designed to take special care at such points while interacting with the cyclists. The algorithms can be designed which consider such limitations. Such modelling is a pre-requisite for a zero-vision road traffic fatality and uptake of this sustainable travel mode.

4.6.8. Vehicle manoeuvre

Table 4.31. Vehicle manoeuvre and crash rate

Vehicle Manoeuvre	*f*	C_R
Changing lane to left	12	0.4
Changing lane to right	28	0.8
Going ahead left hand	40	1.2
Going ahead other	2653	79.8
Going ahead right hand	70	2.1
Moving off	50	1.5
Overtaking moving vehicle	22	0.7
Overtaking on nearside	40	1.2
Overtaking stationary	32	1.0
Parked	1	0.0
Reversing	4	0.1
Slowing or stopping	29	0.9
Turning left	88	2.6

Turning right	236	7.1
U turn	4	0.1
Waiting to go ahead	3	0.1
Waiting to turn left	3	0.1
Waiting to turn right	5	0.2
Total	3325	100.0

Any infrastructure location requiring mergence, divergence or crossing manoeuvre of two or more road users is a potential conflict. These conflict points are highly undesirable and need to be minimized as they cause delay in Traffic (requiring defining or assigning priority) and contribute to road traffic crashes (Malik *et al.*, 2016). Therefore, analysis of the manoeuvre performing during the crash is critical, as most of the crashes (>93%) involve cyclist's interacting with motorists. The detailed manoeuvres and their relative crash rates are presented in Table 4.31. In 80% of the cases, the cyclists and the other vehicle are moving ahead together, followed by 10% of the crashes involving turning movements. These findings depict that the cyclist safety analysis/infrastructure design is much more complicated than just assigning the right of way or defining the priority.

4.7. Chapter Summary

This work investigated the traffic flow, lighting, meteorological, and bicycle use depending upon the rider attribute in the study area. The spatial, temporal variation of crashes is also determined and crash variation by the micro-infrastructure variable. It is found that the cyclist flow varies with the hour, day, and month of journey. These three variables can be used to represent the traffic flow regime plying. The lighting and meteorology conditions are highly varied in the study area. The number of lighting hours in June is 2.6 times higher than in December. Eighty-one per cent of cyclist flow occurs during daylight, whereas only 19% occurs during darkness. Similarly, the minimum precipitation occurs in May (109 mm) and maximum in April (1090 mm).

The number of cycle trips increases with the age group from 0-49 (maximum for 40-49), and then decreases significantly with age (lowest for 70+ age group). The number of cycle trips undertaken by males is three times higher than females. A similar pattern is observed for the average distance traversed per person, with males riding four times longer than females.

There are 3,325 bicyclist crashes reported in the study area between 2005 and 2018, with 79.3% as slight, 19.9% serious, and 0.8% as fatal. The crash rate is highly varied with the hour, month, and day of the journey. Most crashes (83.3%) occur during daylight, and for the crashes occurring in darkness, 88% had the streetlight present and lit. In more than 90% of the cases, the crash occurs in fine weather without high winds, followed by 7% in rainy meteorological conditions. In only 1.8% of crashes, the high winds are present. The road surface conditions are dry in 82% of crashes, contrary to the meteorological conditions, which have dry weather in 92% of crashes. The crash rate is very high for the young population; the under 17 age group constitute 43% of crashes. The crash rate decreases continuously with the age group, with the least reported crashes for > 70. A higher proportion of males crashes (87%) are reported than females. The single bicycle crash only accounts for 6.3% of crashes, whereas 93.7% of crashes involve interaction with other vehicles, multiple vehicle account for less than 4%. The crash rate is varied depending upon road type, junction types, controls, and junction location.

There is a discrepancy between the crash rates and infrastructure usage based upon rider age, gender, and environmental conditions. This validates the results from the literature, which identify these as critical safety variables. These will be modelled in the corresponding chapters.

Chapter 5.

Derivation and model development of the interaction of the age of the rider with safety

5.1. Introduction

This chapter aims to develop a fundamental understanding of one of the reported dynamic variables: the trip maker's personal attribute, i.e., the rider age. This is motivated by the fact that this variable has been reported as a significant variable in the literature, but there are still very few works that deal with modelling this variable. Besides, it is shown that motorists exhibit behavioural sensitivity to the bicyclist appearance (Walker, 2007). Consequently, it is critical to understand how the rider age affects their natural road environment's safety. By modelling this variable, it is expected that the knowledge obtained can be utilized for better design and planning of cycling infrastructure based upon its intended users. We propose a knowledge-driven approach for infrastructure planning based on specific users rather than generalized infrastructure usage. A hybrid approach combining a range of statistical and supervised deep neural learning methodologies is applied. More precisely, this chapter deals to:

- Develop an understanding of how safety is affected by the age group of the rider.
- Test the hypothesis that the unsafeness of interaction between a user and infrastructure depends on the rider age.
- Develop a predictive dynamic safety model with age as an output variable.
- Develop a statistical variable interaction model for a rider age.
- Identify the most important variables affecting the unsafeness of an age group.
- Validate the importance of the identified variables statistically.

In the next section, the traditional statistical model is developed and heatmaps in Section 5.3. In Section 5.4, the predictive deep learning model is extensively described. The importance of different input variables and how they affect a particular age group's safety is presented in Section 5.5, the linear regression model in Section 5.6, and model significance in Section 5.7. Finally, some conclusions are drawn in Section 5.8.

5.2. Statistical model

The traditional statistical model, consisting of traditional crash rates, is presented in Table 5.1, with the rider age divided into eight groups (under 17 to >70). The relative risk is calculated for each group based upon their respective crash frequency and miles traversed. The corresponding normalized risk for each group is calculated with respect to the safest age group age (50-59).

Table 5.1. Variation of statistical risk with riders age

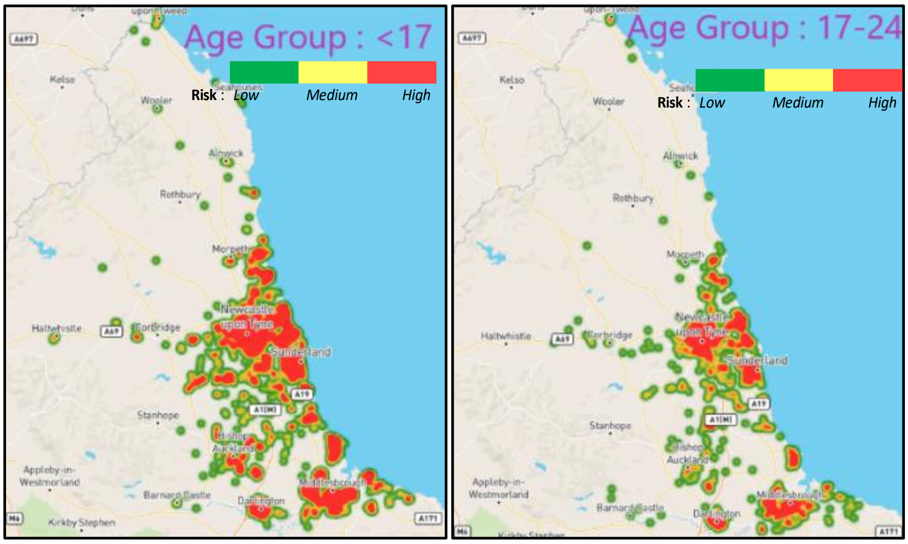
Age group	M_P	M_T	C	R	$N_R = GR/S_F$
0-16	21.3	276.8	1420	5.1	22.8
17-20	67.5	196.4	312	1.6	7.0
21-29	55.6	425.6	481	1.1	5.0
30-39	82.6	713.8	422	0.6	2.6
40-49	85.5	699.4	307	0.4	1.9
50-59	84.1	740.9	167	0.2	1.0
60-69	44.2	306.2	76	0.2	1.1
70+	17.2	151.0	40	0.3	1.1
Total	n/a	3510.2	3225	n/a	n/a

where M_P = Miles per person, M_T = Total miles traversed, C = Crash Frequency R = Risk = crashes/million miles traversed, N_R = Normalized risk = Group risk/ risk of the safest group

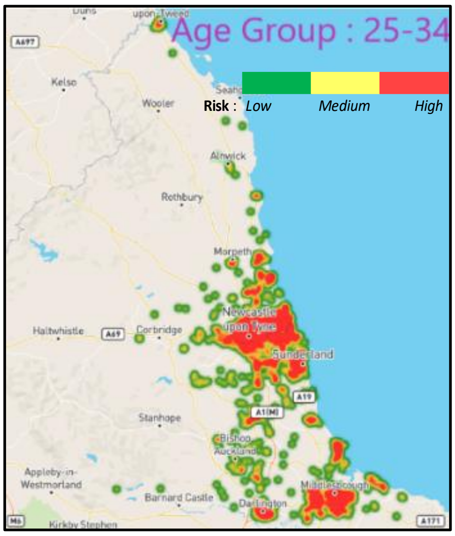
The risk (crashes per million miles) and normalized risk lead to infer that the cyclist's risk decreases with age. The risk faced by the youngest age group (under 17) is 23 times higher than that of the safest age group (50-59) for the same distance traversed. The risk for the cyclist continues to decrease with age, from 17 to 59. However, the elderly population (age >60) face a proportionally slightly higher risk than the preceding age groups. This can be attributed to physical and cognition limitation with advanced age. These results agree with the results obtained in other European countries. Similar results for the young and elderly population are obtained in Italy (Potoglou *et al.*, 2018) and Netherlands (Mindell, Leslie and Wardlaw, 2012). In the UK, London's naturalistic study found daily near-miss incidence rate for cyclist decreases with the rider age (Aldred and Goodman, 2018). These near misses are reported to be correlated with the crash frequencies. It can thus, be concluded that the risk for cyclists decreases with the age of the rider. There are underlying factors that contribute to a decrease in normalized risk with age. These include reducing risk taking behaviour with age, better control, experience, and behavioural sensitivities of other road users with the rider's appearance. The motorists have been found to exhibit behavioural sensitivity to the bicyclist appearance (Walker, 2007) and change their behaviour of interaction with the cyclist based upon the riders' own attributes. Therefore, age is a multilayer variable affecting cyclist safety in multiple ways, requiring in-depth modelling.

5.3. Heat Maps

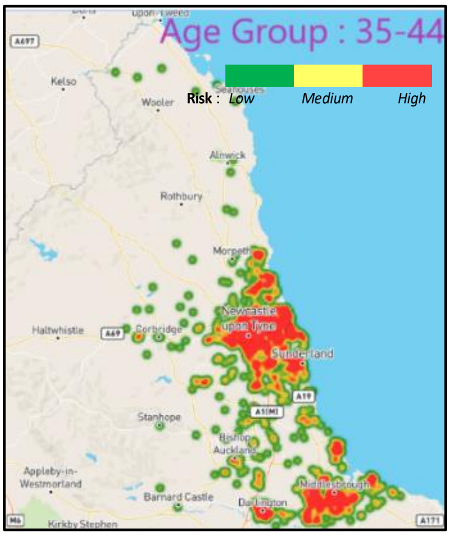
To test the hypothesis that the unsafeness of the interaction between the rider and infrastructure depends on the age of the user, the following risk heat maps are developed for each age group in the investigation area.



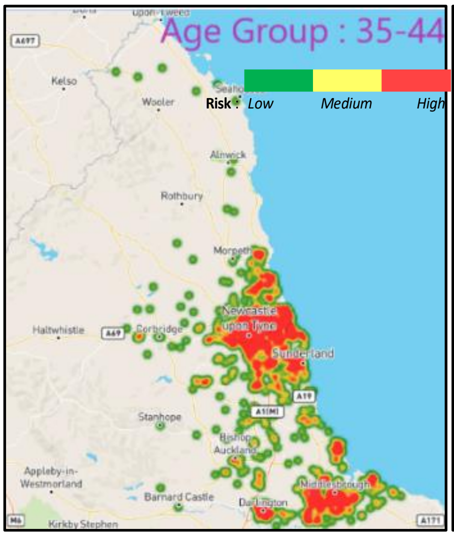
a) b)



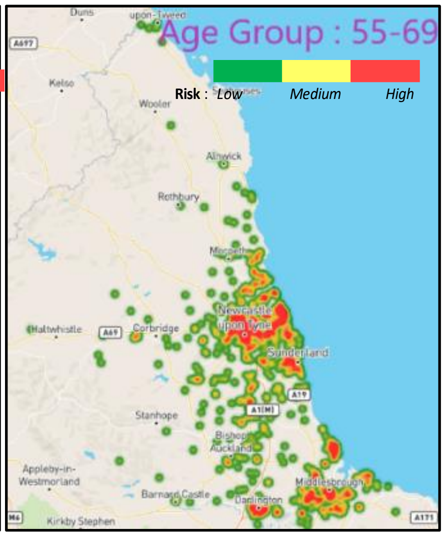
c)



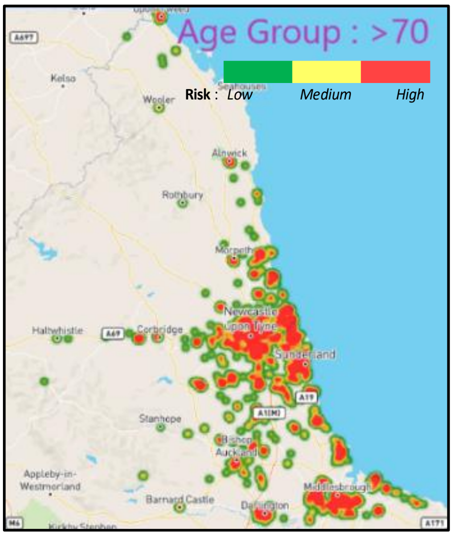
d)



e)



f)



g)

Figure 5.1. Hotspot identification: a) under 17, b) 17-24, c) 25-34, d) 35-44, e) 45-54, f) 55-69, g) over 70

The heat maps demonstrate that the risk that infrastructure presents to riders is dependent upon their age. There is an expected centralization in Newcastle city centre, as it has a higher cyclist flow than other parts of the study area. Similar results for the city centre have been reported in the literature for university towns (see Gatersleben and Appleton, 2007). For the rest of the study area, the pattern and spread of the crashes are different for different age groups. Each of the heatmaps has a different pattern, spread and centralization, that leads to conclude the each of the identified age groups use the infrastructure different, resulting in a varied safety for each age group. The naturalistic study on cyclists in Germany found that microscopic traffic parameters are significantly different for riders belonging to different age groups (Schleinitz *et al.*, 2017). There are location specific infrastructure parameters that determine the risk, affecting cyclists differently. The cyclist attributes also influence their interaction with the infrastructure, i.e. the same infrastructure can pose varying risk levels to users belonging to different age groups. Therefore, it can be concluded that not only infrastructure is a dynamic variable, but also the age of the rider is a dynamic variable affecting its safety.

The findings are contrary to the variables modelled in the present road safety models. The critical variables modelled in the American/Canadian crash prediction model is the Annual Average Daily Traffic (AADT) on minor and major road (AASHTO, 2010)**.** British crash prediction model takes AADT and the investigated infrastructure's length as input variables (Connors *et al.*, 2013). Similarly, the Danish model takes AADT and road geometry (Greibe, 2003). Land use pattern and hierarchy of road are the variables considered by the Swedish crash prediction model (Jonsson, 2005). TRAVA, i.e., the Finnish crash model, considers speed limit, number of intersections, lighted, paved road, sight distance, congestion, number of vehicles and percentage of heavy vehicles (Peltola and Kulmala, 2010). These conventional road safety models are ill-equipped to the specific and peculiar needs of the cyclist. An in-depth safety predictive model is developed in the next section for the cyclist, modelling dynamic input variable of 'age of the rider'.

5.4. Deep learning neural model

A deep learning neural model is constructed based on the literature's identified critical variables to predict the riskiest age group. The model features are described in Table 5.2. The ROC curve, gain and lift charts developed for the constructed model are plotted in Fig. 5.3. The AUROC values are presented in Table 5.3 to establish the model credibility by evaluating its distinguishable power to predict the riskiest age group accurately.

An ROC curve (receiver operating characteristic curve) is a graph that depicts a classification model's performance over all categorization thresholds. It is a graphical representation of a system's diagnostic capability as its discriminating threshold is modified. It is made up of two parameters: a) True Positive Rate, also known as sensitivity, recall, or probability of detection, and b) False Positive Rate, also known as probability of false alarm , computed as (1 -specificity). The true positivity rate and false positivity rate are plotted on a ROC curve at various categorization levels. As a result of the comparison of the two operating characteristics, it is also known as a relative operating characteristic curve. It can also be though as a plot of the power as a function of the decision rule's Type I Error (when the performance is calculated from just a sample of the population, it can be thought of as estimators of these quantities). The AUROC (Area Under the ROC Curve) is a two-dimensional measurement of the full area beneath the ROC curve. A model with 100% incorrect predictions has an

AUROC of 0, whereas one with 100% right predictions has an AUC of 1. There are two primary reasons for using the AUROC value: a) it is scale-invariant, which means it measures how well predictions are ranked rather than their absolute values, and b) it is classification-threshold-invariant, which means it measures the quality of the model's predictions regardless of which classification threshold is used. Gain and Lift charts are used to assess classification model performance. They assess how much better one may anticipate to do with a predictive model than without one. Gain at a given decile level is the ratio of the total number of targets in the data set to the cumulative number of targets up to that decile. It quantifies how much better one may anticipate to do with a predictive model vs without one. At a particular decile level, lift is defined as the ratio of gain percent to random expectation percent. The larger the distance between the lift curve and the baseline, the more accurate the model.

Table 5.2. Model features of the constructed deep learning model

		Sample Size	**Percentage**
Sample	Training	2108	65.4
	Validation	954	29.6
	Holdout	163	5.0
Total		3225	100.0
Dependent Variable: Driver Age Group			
Input Layer	Number of Units	172	
Hidden Layer(s)	Number of Hidden Layers	2	
	Number of Units in each Hidden Layer	350	
	Activation Function	Hyperbolic tangent	
	Error Function	Cross-entropy	

	Cross-Entropy Error	252.7
Output Layer	Dependent Variables	Driver Age Group
	Number of Units	7
	Activation Function	SoftMax
	Error Function	Cross-entropy
	Cross-Entropy Error	1392.2

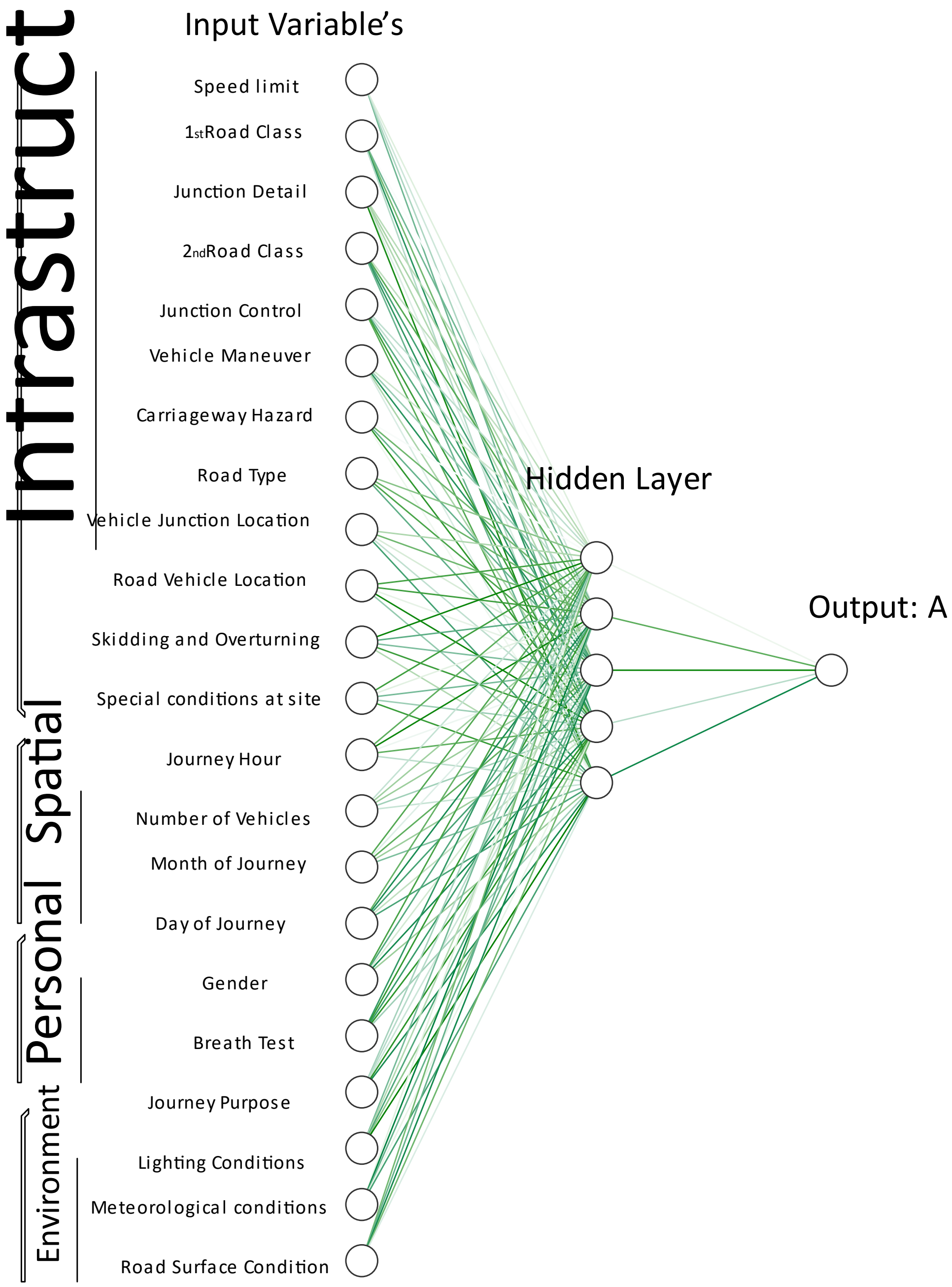
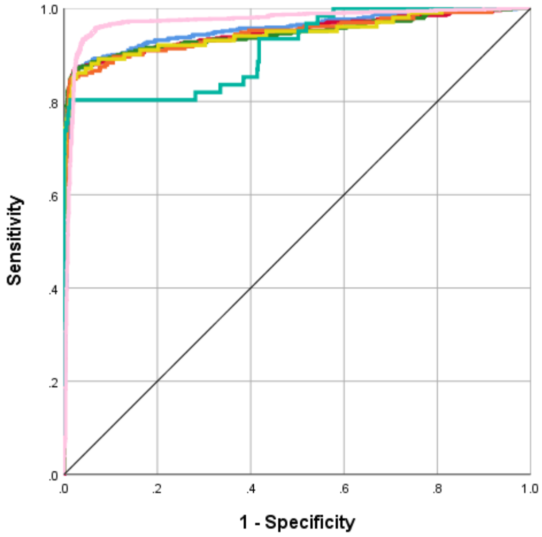
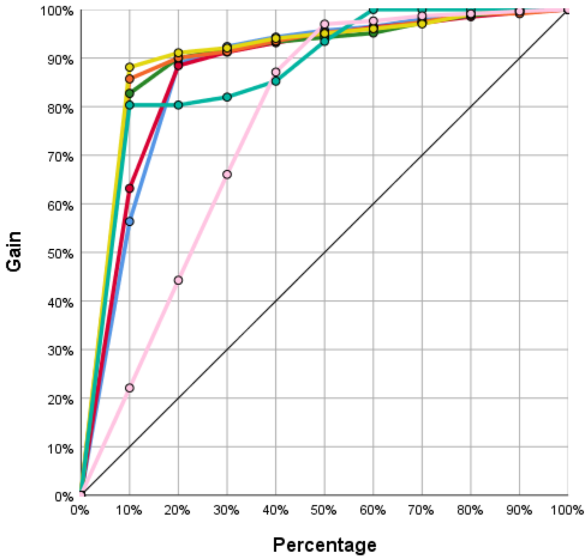


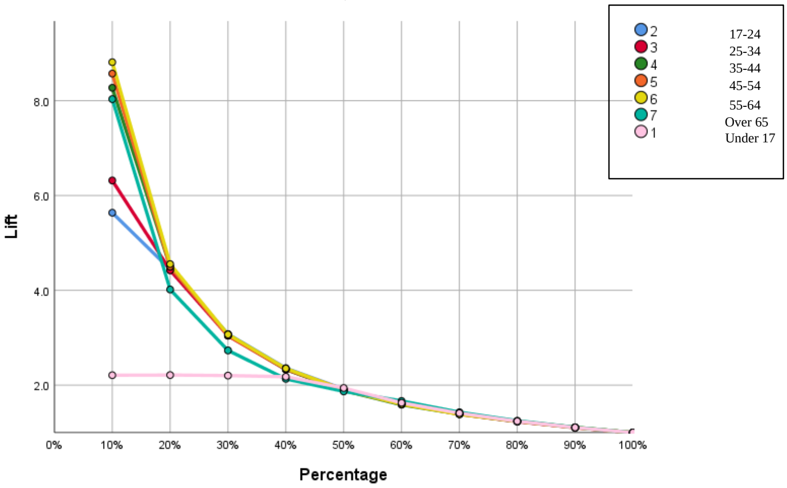
Figure 5.2. Abstract representation of the predictive deep learning model



a)



b)



c)

Figure 5.3. Model characteristics: a) ROC curve, b) Gain chart, and c) Lift chart for the constructed deep learning model

Table 5.3. Area under the receiver operating curve (AUROC) for output variable

Variable	AUROC	Variable	AUROC
Under 17	0.97	45-54	0.95
17-24	0.95	55-64	0.95
25-34	0.95	Over 65	0.91
35-44	0.95	Average	0.95
St. dev	0.02	Median	0.95

The AUROCC values obtained for over 65 (91%), 55-64 (95%), 45-54 (95%), 35-44 (95%), 25-34 (95%), 17-24 (95%), and under 17 (97%) age groups, indicate a high distinguishable capability between the risky and non-risky age groups. The accuracy achieved is plausible, considering the multifactor nature of crashes. To further evaluate the prediction capability of the model, gain and lift charts are developed, indicating the model has an excellent prediction capability. Therefore, we can conclude that the developed model can be used efficiently to predict the riskiest age group based upon the specific input variables. There are very few works in literature, which have been able to model the age variable for safety analysis with reasonable accuracy and efficiency.

It is widely reported in the literature that the majority of motorist crash prediction models have a prediction success of less than 50% (Hossain and Muromachi, 2009). The application of TRAVA, i.e., the Finnish crash models for cyclist, revealed an error of greater than 65% (Peltola and Kulmala, 2010). Similarly, Federal Highway Administration FHWA (transportation department of USA) analysis on the safety analysis using the major simulation software's, VISSIM, AIMSUM, TEXAS and PARAMICS (Gettman *et al.*, 2008), revealed that there are modelling inaccuracy in the microsimulations for the cyclist. Lawson *et al.*, 2013, argued that the conventional models are developed for the assignment of the motorized modes of travel and are not equipped for the cyclist needs. These are unable to quantify the effect of the cyclist safety performance function (Lawson *et al.*, 2013). A survey on safety models (Yannis *et al.*, 2015) found that around 70% of the European road agencies rarely or never systematically use the collision prediction model in their decision making owing to these reasons. The constructed model has superiority over the available traditional road safety models in the literature. This is attributed to the ability of the deep learning neural network to model the non-linear and complex relationship between input and output variables.

These present models are usually probability-based. The gain and lift charts evaluate the developed model's distinguishable capability compared to a non-model probabilistic approach (baseline scenario). In the gain chart, all the predicted outcomes are higher than the baseline scenario of 45 degrees, reinforcing the appropriateness of the constructed models. The same is depicted in the lift chart, e.g. in predicting the age group > 70 years, at 10% data points, the accuracy of the model is eight times higher than the base case. The developed safety performance functions are equipped to the particular needs of the cyclist. The model does not require historical crash data for modelling. The various input variables of infrastructure, spatial, personal, and environmental variables can be directly used to model safety once the model has been constructed. It can be applied to an infrastructure that is still in the planning and design phase.

5.5. Variable Importance

The importance of each variable and the normalized importance with respect to the most critical variable are calculated and tabulated in Table 5.4. The most significant variable affecting the risk for an age group is the *rider journey purpose.* This is followed by the hour of the journey, a spatial variable representing the *traffic flow regime*. They are followed by vehicle manoeuvre and the cycle road location, which are infrastructure variables that define cyclist interaction *with the infrastructure.* The *lighting conditions* that the cyclist is subjected to impact cyclists' safety, varying with the rider age. This is an expected result as to how different age groups react to different lighting conditions is dependent upon their experience, physical and cognitive capabilities. This is followed by the month of the journey (a spatial variable representing a combination of traffic flow regime and journey purpose), meteorological conditions, junction location of the vehicle, junction details, breath test (intoxication), speed limit, number of vehicles, special conditions at the site, carriageway hazard, day of the journey, road type, and first road class. These are mainly infrastructure variables. Therefore, implying that the riders from different age groups interact differently with the different road infrastructure. The variable importa-

Table 5.4. Normalized importance of the input variables

Variable	I	N_I (%age)
Journey Purpose of rider	0.058	100.0
Hour	0.054	92.8
Vehicle Manoeuvre	0.052	88.3
Road Location of Vehicle	0.049	83.7
Light Conditions	0.046	78.9

Month	0.045	76.9
Weather	0.045	76.7
Junction Location of Vehicle	0.045	76.3
Junction Detail	0.044	75.6
Breath Test	0.043	74.2
Speed Limit	0.043	72.9
Number of Vehicles	0.043	72.8
Special Conditions at Site	0.042	72.1
Carriageway Hazards	0.042	71.4
Day	0.041	70.6
Road Type	0.040	69.0
1st Road Class	0.040	68.9
2nd Road Class	0.039	67.5
Road Surface Condition	0.037	62.5
Skidding and Overturning	0.036	61.3
Junction Control	0.034	58.1
Driver Gender	0.027	46.3
Weekday or Weekend	0.027	45.8

where I = Importance, and N_I = Normalised Importance

-nce from the constructed deep learning model, risk rates, and hotspot heat maps, led us to conclude that infrastructure poses a different risk to the rider based upon its age. The study results can have significant implications on the policy, design, and planning of the road network. The present models do not consider the variable age. These are based upon the assumption that road safety is independent of age. The cyclist age distribution can vary significantly from one place to another. Therefore, the research can help develop focused remedial measures to improve safety based for the intended users, rather than the average usage of the infrastructure at an aggregate level such as country.

The association between the target and input variables is tested statistically through the chi-square test in Table 5.5. Their strength of association with a rider age group is determined using Cramer V value and Cohen table in Table 5.6.

Table 5.5. Chi-square test for testing the statistical association between the input variables and rider age group

Null Hypothesis H_0 Driver Age risk is Independent of	Alternate Hypothesis H_1 Driver Age risk is dependent on	Pearson Chi-Square χ^2	D_f	*p*-value	H
Journey Purpose of rider		520.95	30	0.01	H_1
Hour		678.6	138	0.01	H_1
Vehicle Manoeuvre		309.7	102	0.01	H_1
Road Location of Vehicle		190.2	42	0.01	H_1
Light Conditions		203.7	48	0.01	H_1
Month		167.8	66	0.01	H_1
Weather		74.2	48	0.01	H_1
Junction Location of Vehicle		208.7	48	0.01	H_1
Junction Detail		232.0	48	0.01	H_1
Breath Test		224.9	36	0.01	H_1
Speed Limit		265.4	30	0.01	H_1
Number of Vehicles		238.7	24	0.01	H_1
Special Conditions at Site		134.5	30	0.01	H_1
Carriageway Hazards		757.7	24	0.01	H_1
Day		103.1	36	0.01	H_1

Road Type	170.0	30	0.01	H_1
1st Road Class	368.4	24	0.01	H_1
2nd Road Class	131.7	30	0.01	H_1
Road Surface Condition	97.2	18	0.01	H_1
Skidding and Overturning	67.3	18	0.01	H_1
Junction Control	53.25	18	0.01	H_1
Driver Gender	10.28	6	0.11	H_0
Weekday or Weekend	15.8	6	0.02	H_1

where D_f = Degree of freedom, H = Hypothesis adopted. H_0 = Null hypothesis, i.e., the risk for a rider belonging to a particular age group is independent of the variable, H_1 = Alternate hypothesis, i.e., the risk for a rider belonging to a particular age group is dependent on the variable, χ^2 = Pearson chi-square value.

Table 5.6. Quantifying the association type between the input variables and rider age group

	V	p-value	$Df = (R-1) \wedge (C-1)$	A_T
Journey Purpose of rider	0.18	< 0.01	$(7-1) \wedge (6-1) = 5$	M
Hour	0.18	< 0.01	(7-1) ∧ (23-1) = 6	M
Vehicle Manoeuvre	0.13	< 0.01	(7-1) ∧ (18-1) = 6	M
Road Location of Vehicle	0.09	< 0.01	(7-1) ∧ (8-1) = 6	S
Light Conditions	0.1	< 0.01	(7-1) ∧ (7-1) = 6	S
Month	0.09	< 0.01	(7-1) ∧ (12-1) = 5	S
Weather	0.06	0.009	(7-1) ∧ (9-1) = 6	S
Junction Location of Vehicle	0.1	< 0.01	(7-1) ∧ (9-1) = 6	S
Junction Detail	0.11	< 0.01	(7-1) ∧ (9-1) = 6	S

Breath Test	0.11	< 0.01	(7-1) ∧ (4-1) = 3	S
Speed Limit	0.13	< 0.01	(7-1) ∧ (6-1) = 5	M
Number of Vehicles	0.14	< 0.01	(7-1) ∧ (5-1) = 4	M
Special Conditions at Site	0.09	< 0.01	(7-1) ∧ (6-1) = 5	S
Carriageway Hazards	0.07	< 0.01	(7-1) ∧ (5-1) = 4	S
Day	0.07	< 0.01	(7-1) ∧ (7-1) = 6	S
Road Type	0.10	< 0.01	(7-1) ∧ (6-1) = 5	S
1st Road Class	0.17	< 0.01	(7-1) ∧ (5-1) = 4	M
2nd Road Class	0.09	< 0.01	(7-1) ∧ (6-1) = 5	S
Road Surface Condition	0.1	< 0.01	(7-1) ∧ (4-1) = 3	S
Skidding and Overturning	0.08	< 0.01	(7-1) ∧ (4-1) = 3	S
Junction Control	0.07	< 0.01	(7-1) ∧ (4-1) = 3	S
Driver Gender	0.05	0.113	(7-1) ∧ (2-1) = 1	n/o
Weekday or Weekend	0.07	< 0.01	(7-1) ∧ (2-1) = 1	S

where V = Cramer V value, and Df = degree of freedom, A_T = Type of Association, S = Small, M = Medium, *n/o* = no association.

A significant correlation exists between all the identified variables and age group at a 99.9% confidence interval, except the rider gender. From the deep learning variable importance model, rider gender is the second least important variable. A medium correlation strength is obtained for the first three most important variables, i.e. journey purpose, the hour of journey, vehicle manoeuvre. Besides, medium association strength is also obtained for two infrastructure variables of the speed limit and first road class and a spatial variable of the journey hour. For the rest of the variables, a small strength correlation is achieved, i.e., for lighting conditions, month and day of the journey, meteorological conditions, junction details and control, junction location of vehicle, intoxication, special condition, carriageway hazard, road type, second road class, road surface condition, skidding and overturning. The results indicate that no single variable has a high strength of correlation with the rider age, which affects its safety. A single high correlation would have been contrary to the established road traffic crash modelling theories (Sabey and Taylor, 1980; Carsten *et al.*, 1989). The statistical analysis of the identified variables has validated the results obtained by deep learning neural networks and the initial choice of the variable selected for analysis based upon the review of the literature. The three spatial variables of journey purpose, the hour of the journey and the number of vehicles have a medium strength of association. This signifies that the spatial variation in terms of journey purpose, traffic flow conditions are critical variables that affect the safe usage of the infrastructure for a particular age group.

5.6. Linear regressions

The linear regression modelling results are described in Table 5.7 and Equation 5.1, respectively.

Table 5.7. Linear regression model

Variable	Coefficient	*S.E*	*B*	*t*	Sig.	95% *C.I B*	
						L_L	U_L
(Constant)	44.12	2.72		16.23	0.00	38.79	49.44
Rider gender	0.67	0.81	0.01	0.82	**0.41**	-0.92	2.26
Hourly Flow rate	-1.21	0.23	-0.17	-5.16	0.00	-1.67	-0.75

Flow Regime	1.81	0.81	0.13	2.23	0.03	0.22	3.40
Peak	-0.75	1.38	-0.02	-0.54	**0.59**	-3.45	1.96
Month Flow Rate	0.16	0.16	0.03	1.00	**0.32**	-0.15	0.46
Monthly Precipitation in mm	-0.07	0.03	-0.04	-2.14	0.03	-0.13	-0.01
Monthly Lighting hours	-0.37	0.11	-0.08	-3.23	0.00	-0.59	-0.14
Collision Severity	2.31	0.60	0.06	3.83	0.00	1.13	3.49
Number of Vehicles	-7.75	0.79	-0.16	-9.83	0.00	-9.30	-6.21
Hour	-0.68	0.06	-0.19	-10.88	0.00	-0.80	-0.55
Speed Limit	0.35	0.03	0.21	12.45	0.00	0.29	0.40
Road Hierarchy level and direction	-1.21	0.17	-0.11	-6.95	0.00	-1.56	-0.87

where B = Standardized coefficient Beta, $S.E$ = Standard error, 95% $C.I$ B = 95% Confidence interval of B, L_L = Lower limit, and U_L = Upper limit.

$$RRA = a_0 - a_1x_1 + a_2x_2 - a_3x_3 - a_4x_4 + a_5x_5 - a_6x_6 - a_7x_7 + a_8x_8 - a_9x_9 \tag{5.1}$$

where RRA = Riskiest rider age, x_1 = Hourly flow rate, x_2 = Flow regime, x_3 = Monthly precipitation, x_4 = Monthly flow rate, x_5 = Collision severity, x_6 = Number of vehicles, x_7 = Hour of the journey, x_8 = Speed limit, and x_9 = Change in the road hierarchy level.

The estimated coefficient values $a_0, a_{1,}, a_2, a_3, a_4, a_5, a_6, a_7, a_{8,}$ and a_9 values are 44.1, 1.2, 1.81, 0.07, 0.37, 2.31, 7.75, 0.68, 0.35, and 1.21 respectively

Three variables are not statistically related with the riskiest rider age:

a) Rider gender,
b) Whether the journey is being made in the peak hour or not, and
c) Monthly flow rate.

All the other variables, such as hourly flow rate, traffic flow regime, monthly precipitation, monthly lightning hours, the severity of the collision, number of vehicles, the hour of journey, speed limit and road hierarchy level and direction, are statistically associated with the riskiest rider age. The variables of hourly flow rate, monthly precipitation, number of vehicles, and a sudden change in the road hierarchy level have a negative relationship, implying their increase results in a relatively safer environment for the older population. In contrast, variables such as the flow regime, collision severity, and speed limit have a positive relationship, implying as these variables increase, the relative risk for the older population increases

As the hourly flow rate increases, safety for the older population increases. Similarly, as the number of lighting hours increases, the number of vehicles interacting with the rider increases, resulting in relative safer conditions for the older populations than the younger riders. With the increase in the road hierarchy level, i.e. a more remarkable change in the functional road hierarchy level, the older population's relative safety increases. Therefore, it can be inferred that the older generation are better equipped due to experience and knowledge of the road network to a sudden change in the road functional type or an increase in the traffic flow. Such a change can result in a challenging behaviour of the other road users, e.g. sudden braking by the motorists to confer to a lower speed limit, which can further result in swearing, a strong wind gust for the cyclists to negotiate, which itself is also adapting to this sudden change in infrastructure functional toad type, and more conflicts. The younger riders may have the physical skills, but older riders possess experience, knowledge of the route and recognize such potential hotspots in their everyday journey. However, the older population is more susceptible to severe and fatal injuries than the younger population due to the physiological abilities of the younger population to respond better to any abrasion or physical injury, with a lower impact on their physical health.

5.7. Modelling framework significance

At present, the safety analysis is mainly performed at the macro level, such as country level, and demographics of the intended users are ignored, e.g. a university town such as Oxford may have a different population demographics than an old English mining town such as Sunderland. The study results demonstrate that if we undertake such modelling without considering the age distribution, it will lead to inaccurate modelling. Hence, a single countrywide model without considering the age distribution of a particular area such as a city or a county will lead to improper modelling and corresponding inaccurate recommendation measures. Such a model may be appropriate for motorists, who benefit from a machine at their disposal. The physical and cognitive abilities of a motorist do not get severely strained as a cyclist, nor is the maturity and ability to respond to the riskiest situation such a critical safety variable.

One of the significant drawbacks of the present road safety model is that very few can be applied in the planning stages due to their dependence on the traffic flow and historical crash data. The facility in the planning stages may not necessarily have the requisite traffic flow data. If the facility is in the planning stage, it will not have any crash data either. The application of such models is questionable in the planning stage or for a redeveloped scheme. This has led to the omission of road safety variables in the planning, negatively affecting safety. The developed model depends on the spatial variables, personal attributes, environmental conditions, and infrastructure variables. Hence, it can be used to model safety for such infrastructure schemes in planning stages, thereby contributing to the inclusion of the safety variable in the infrastructure's planning and design.

Numerous studies have questioned the present modelling and their ability to model the cyclists' idiosyncratic needs (Calvey *et al.*, 2015; Lawson, 2015). The hybrid methodology proposed and applied in the Tyne and Wear not only models safety accurately but also develops the understanding of the interaction of the variables and how they affect safety. These attributes, such as the journey purpose, traffic flow regime, and infrastructure parameters, are all dynamic variables unique to a cyclist. Therefore, there is a need to develop the models specifically for the cyclist using such an intelligent hybrid methodology based upon deep neural networks, demonstrated as an effective method of modelling safety and understanding variable interactions to affect the cyclist safety. Hence, we can conclude that the present methodologies, such as probability or regression-based, need to be replaced. Such a shift in modelling will result in a better understanding of cycling safety, identifying the crash causation, knowledge-driven recommendation measures, and an integrated sustainable transportation system. Such studies have a renewed focus as we move towards the pathway for the autonomous transportation system. The cyclist variabilities modelled in the work can be inputted into the V-V (vehicle to vehicle) and V-I (vehicle to infrastructure) algorithm for autonomous vehicles. These algorithms will consider the rider variability in a specific age group at the critical infrastructure type or the particular environmental/ spatial conditions.

The local authorities can also use the model to plan, design, and optimize the cycling network based upon the intended population (age distribution) and model the safety considering the infrastructure, environmental, spatial and other personal attributes of gender and journey purpose. The constructed models model also considers the land use pattern, the peak, staggered peak, and other dynamic variables varying from city to city. The model can be interoperable to a different city/ country, as cycling safety factors are not expected to change significantly. However, there may be variations in the significance importance of the variables. Therefore, before applying the model to different scenarios, it needs to be validated, similar to all the major simulation packages.

5.8. Chapter Summary

In this chapter, one of the critical safety variable affecting the safe usage of infrastructure, “age of the rider”, is modelled. An accurate dynamic road safety model is constructed, and an understanding of the critical parameters affecting cyclist's safety is developed. The average distinguishable power of the constructed deep learning model to accurately predict the riskiest age group is 95%, with a standard deviation of 0.02, implying a high prediction accuracy across all the age groups.

It is found that the cyclist's risk decreases with age, e.g. riders under the age of 17 are 23 times more likely to be involved in a crash than the age group of 50-59 for the same distance traversed. It is postulated that the older population is better equipped to negotiate a sudden change in the functional road type and higher traffic flow due to the road network's experience and knowledge. However, the older population is more susceptible to severe and fatal injuries than the younger population. The age of the rider influences other road user's interaction with the cyclist. The rider gender and age are two independent variables that do not have underlying casualty nor statistical association. Hence, the rider gender needs to be modelled separately (Chapter 6). The spatial variation in journey purpose and traffic flow conditions are critical variables affecting the safe usage of infrastructure for a particular age group. The following are the most critical variables affecting the safe usage of infrastructure for an age group:

a) Personal Characteristics (Journey Purpose),

b) Traffic flow regime (Hour of journey),

c) Infrastructure Manoeuvre and location of the rider on the infrastructure

d) The environmental condition of variable lighting conditions

e) The month of the journey (representation of the journey purpose and flow regime)

f) Environmental conditions of variable meteorological conditions

g) Other infrastructural variables (junction location, junction details, speed limit).

The present research in road safety modelling needs to move from simple probability-based models to deep learning neural models, which can open new possibilities, as demonstrated in this work. The study results can significantly impact the route choice, modelling, and planning of infrastructure.

Chapter 6.

Derivation and model development of the interaction of the gender of the rider with safety

6.1. Introduction

This chapter proposes a nanoscopic safety modelling framework for cyclist road infrastructure. To achieve the objective, an intelligent hybrid modelling framework combining i) traditional statistical, ii) data learning, iii) critical variable significance, and iv) logistic regression methods is developed. The literature widely reports that the rider personal attributes of age and gender affect their safe usage of infrastructure. In Chapter 4, the age variable was modelled. This chapter aims to develop a fundamental understanding of the other reported dynamic personal attribute, i.e., rider gender. There are very few works that have attempted to model this variable (Walker, 2007). Hence, it is aimed to develop an accurate road safety model that can predict the riskiest rider personal attribute and understand how different variables affect the safe usage of an infrastructure for a particular rider. More precisely, the objectives of this chapter are to:

1. Test the hypothesis that the unsafeness of the interaction between the user and infrastructure is dependent upon rider attributes.

2. Develop an intelligent framework that can develop a predictive model and identify the critical variables affecting safety.

3. Construct a nanoscopic safety model with the riskiest gender and age group as output.

4. Identify the significance of the variable affecting the unsafeness of the rider based upon the personal attribute.

5. Develop a statistical variable interaction model

In the next section, traditional statistical models are developed, and heat maps in Section 6.3. In Section 6.4, the predictive deep learning models are developed. The importance of different input variables and how they affect a particular age group safety is postulated in Section 6.5 and the logistic model in section 6.6. Finally, some conclusions are drawn in Section 6.7

6.2. Traditional statistical model

The traditional probability-based statistical model with the output of risk and normalised risk rate is presented in Table 6.1. The safest age group for both males and females is 50-59, whereas, across gender, the safest age group is 50-59 females. The normalised risk is calculated for each group with respect to its safest age groups and normalised risk across gender with respect to the 50-59 female age group. The relative risk faced by the rider of a different gender for the same age group is presented in Table 6.2.

Table 6.1. Traditional probability based statistical model

Age group	M_p	P	M_T	C	R	RN_G	RN_O
Male							
0-16	30.4	6.7	203	1272	6.28	22.95	90.87
17-20	128.3	1.5	192	285	1.48	5.43	21.49
21-29	65.4	3.9	256	418	1.64	5.98	23.67
30-39	132.4	4.3	568	368	0.65	2.37	9.37
40-49	146.0	4.1	592	267	0.45	1.65	6.53
50-59	130.7	4.3	567	155	0.27	1.00	3.96
60-69	72.9	3.4	246	70	0.28	1.04	4.12
70+	32.6	3.9	128	32	0.25	0.91	3.62
Female							
0-16	11.7	6.3	74	148	2.00	28.91	28.91
17-20	3.2	1.4	5	27	5.97	86.35	86.35
21-29	45.7	3.8	171	63	0.37	5.32	5.32
30-39	33.9	4.4	147	54	0.37	5.30	5.30
40-49	26.3	4.1	109	40	0.37	5.33	5.33
50-59	38.8	4.5	174	12	0.07	1.00	1.00
60-69	17	3.6	60	6	0.10	1.44	1.44
70+	4.3	4.7	21	8	0.38	5.54	5.54

where M_p = Miles per person, P = Population in millions, M_T = Total million miles traversed, C = Crash frequency, R = Risk in terms of crashes per million miles, RN_G = Normalised risk per group, and RN_O = Overall normalised risk.

Table 6.2. Risk rate across age groups for males/females

Age group	C_M		R_R
	Male	Female	
0-16	6.28	2.00	3.14
17-20	1.48	5.97	0.25
21-29	1.64	0.37	4.45
30-39	0.65	0.37	1.77
40-49	0.45	0.37	1.23
50-59	0.27	0.07	3.96
60-69	0.28	0.10	2.87
70+	0.25	0.38	0.65
Average	1.04	0.47	2.22

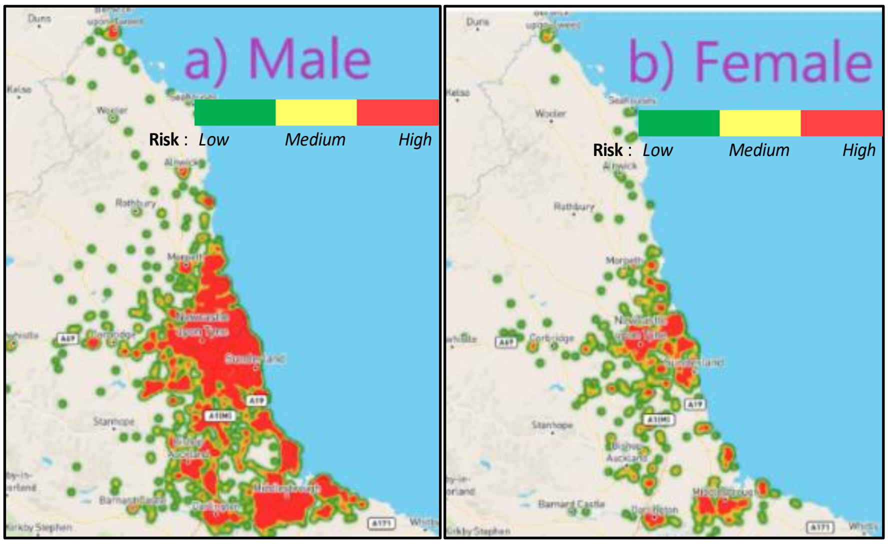
where C_M = Crashes per million miles, R_R = Relative risk of males with respect to females for the same age group.

The risk for male and female riders is 1.04 and 0.47, respectively, per million miles traversed. Across gender, the risk decreases with age. However, the rate at which the risk reduces with age differs significantly depending upon the rider gender. The 50-59 age group is the safest for both males and females, with 50-59 females being the safest overall. The normalised risk is highest for young males, 0-16 age. The young riders (0-16) face a disproportionately higher risk, with male riders facing 23 times and women riders face twice the risk than their respective safest 50-59 age group for the same distance traversed. Adolescent female riders (17 to 20) are the riskiest age group among females, six times riskier than the safest age group. This age group is riskier only for women, though it is relatively safer for men. In the younger and middle-aged population, women cyclists are safer than male cyclists. Elderly females, on the other, face higher risk and form the third riskiest group for females. There are only two age groups in which men rider relatively safer than females, i.e., adolescents (17-20) and the elderly population (>70). However, for the rest of the population (aggregately), it can be concluded that women ride relatively safely than men, with the most significant difference for the 21-29 age group, in which women safety is 4.5 times higher than males. Across the age groups, women riders are 2.2 times safer than males for the same distance traversed.

6.3. Heatmaps

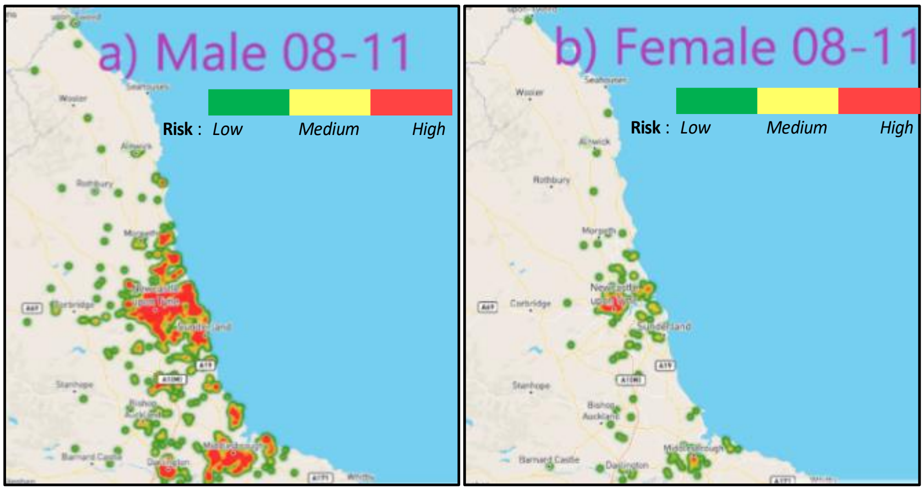
To test the hypothesis that the unsafeness of the interaction between a rider and infrastructure is dependent upon its gender, spatial risk heatmaps are developed (Fig 6.1). For investigating the temporal variation of crashes for different gender, temporal risk heat maps are developed in Fig 6.2, demonstrating the variation of risk across gender for morning and evening peak flows.

It is evident that how different locations act as a hotspot is dependent upon the gender of the rider. There is an expected centralisation in the city centre in Newcastle. Except for the Newcastle city centre, the pattern and spread of crashes are significantly different. It can be inferred that the safe usage of the infrastructure depends upon the gender of the trip maker. After investigating the spatial variation, the temporal variation is investigated in Fig 6.2. The heat maps are generated for the morning (08-11:00) and evening (15:00-18:00) peak hours. The results show that safe usage of the infrastructure is also dependent upon the hour in which the journey is made. Comparing the heatmaps within different peaks shows that the crash spread varies between morning and evening peaks for both males and females. However, the increase in the density and spread is much more considerable for females compared

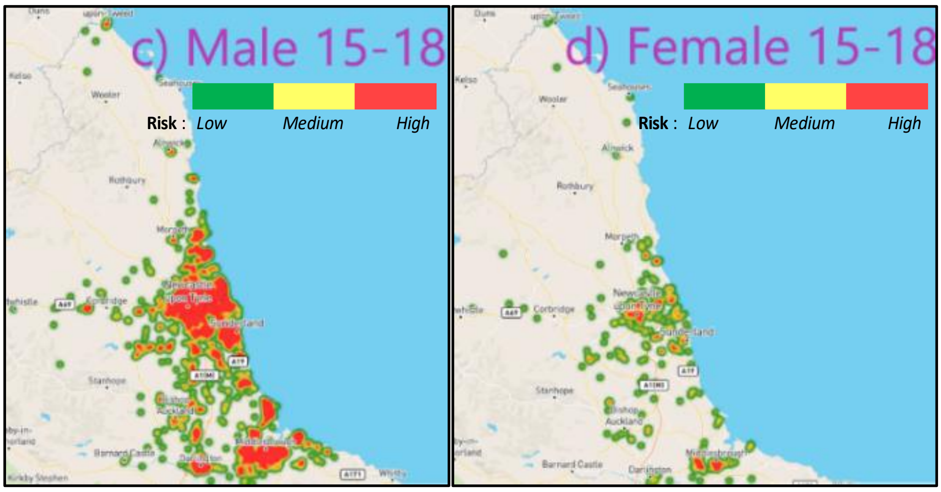


a) b)

Figure 6.1. Heat maps for hotspot identification for a) Male and b) Female



a) b)



c) d)

Figure 6.2. Temporal variation of the crashes for a) male 08:00-11:00, b) female 08:00-11:00 hours; c) male 15:00-18:00, and d) female 15:00-18:00 hours

with males. This lead to infer that both morning and evening peak (traffic flow regime) are temporal variables affecting the cyclists differently. However, such an assertion needs to be validated statistically. The journey hour represents the traffic flow regime, which presents a varied risk to riders of different genders. Beecham, 2013 argued that a female spatial and temporal structure of a journey differs markedly from men (Beecham, 2013). It can hence, be inferred that a women's preference for infrastructure is influenced by the relative safety that the infrastructure presents. As the safety varies temporally and spatially, this makes the route preference to vary similarly.

It is established in Chapter 5 that the risk that a rider faces on the road network depends on its age. Therefore, it can be concluded that not only infrastructure is a dynamic variable, but also the age and gender of the rider are dynamic variables affecting its safety, which vary temporally and spatially. The findings are contrary to the variables modelled in the present road safety models (Table 2.4). Although serving their intended purpose for which they were developed, these conventional road safety models are ill-equipped to the cyclist's unique needs at the nanoscopic level. These results can significantly impact further research, policy, and planning of the cycling road transportation network. As a result, ANOVA is performed for ancillary statistical analysis. Firstly, the age distribution for different infrastructure types is presented in Table 6.3.

The age distribution indicates that different infrastructure types pose a varying risk to the rider based upon its personal attributes. The means are significantly different. For validating these findings statistically, the analysis of variance (ANOVA) is used. ANOVA is based upon the assumption of homogeneity, which needs to be verified before applying. The Levene test is used for testing this assumption of homogeneity

(Agresti, 2018), whose results are presented in Table 6.4. The Levene statistic for the mean (median) is calculated as 1.18 (1.73), and the corresponding significance $p > 0.05$, thereby validating the assumption for the use of ANOVA. The ANOVA results are presented in Table 6.5.

Table 6.3. Age distribution for different infrastructure types

	D	O	R	S	S_L
Mean	31.4	24.9	33.9	23.3	31.5
Std. Deviation	16.6	15.3	15.7	15.3	14.9
Std. Error	1.4	2.1	1.1	0.3	3.6

where *D* = Dual Carriageway, *O* = One way street, *R* = Roundabout, *S* = Single Carriageway, and S_L = Slip Road.

Table 6.4. Levene test

	L_S	df_1	df_2	Sig.
Based on Mean	1.18	4	3207	0.314
Based on Median	1.73	4	3207	0.140

where L_S = Levene statistic, *df* = degree of freedom

Table 6.5. Analysis of variance for the statistical association between the age and type of infrastructure

ANOVA	S_S	df	M_S	F	Sig.
Between Groups	31398.9	4.0	7849.7	33.2	0.00001
Within Groups	757855.9	3207.0	236.3		
Total	789254.8	3211.0			

where S_S = Sum of squares, and M_S = Mean Square

The result from the ANOVA analysis validates the results obtained from the heat maps. The type of road infrastructure has a significant effect on the riskiest age group of the rider, $(F\ 4, 3207) = 33.2\ p < 0.001.$ The F-ratio indicates that different infrastructure types pose a varying degree of risk to the rider belonging to different age groups. ANOVA provides the overall association of the rider's age group with the different types of infrastructure. To estimate the difference within infrastructure types on the riskiest age group; a Post hoc comparison is performed, whose results are presented in Table 6.6. In the multi comparison, the mean difference for the age groups (I-J) is found to be statistically significant ($p < 0.05$) between

i. Dual and single carriageway,
ii. Dual carriageway and one-way street,
iii. One-way street and roundabout,
iv. Roundabout and single carriageway, and vice versa

Table 6.6. Post hoc comparison within the different infrastructure types for the riskiest age group

M_I	M_J	M_{AG} $(M_I$-$M_J)$	Std. Error	Sig.
Dual Carriageway	One way Street	6.5	2.5	0.1
	Roundabout	-2.5	1.7	0.7
	Single Carriageway	8.1	1.3	0.0
	Slip Road	-0.1	3.9	1.0
One way Street	Dual Carriageway	-6.5	2.5	0.1
	Roundabout	-9.0	2.4	0.0
	Single Carriageway	1.7	2.1	1.0
	Slip Road	-6.6	4.3	0.7
	Dual Carriageway	2.5	1.7	0.7

Roundabout	One way Street	9.0	2.4	0.0
	Single Carriageway	10.7	1.1	0.0
	Slip Road	2.4	3.9	1.0
Single Carriageway	Dual Carriageway	-8.1	1.3	0.0
	One way Street	-1.7	2.1	1.0
	Roundabout	-10.7	1.1	0.0
	Slip Road	-8.3	3.7	0.3
Slip Road	Dual Carriageway	0.1	3.9	1.0
	One way Street	6.6	4.3	0.7
	Roundabout	-2.4	3.9	1.0
	Single Carriageway	8.3	3.7	0.3

where M = Mean, and M_{AG} = Mean age difference = M_I - M_J

The diverse infrastructure types require varying physical manoeuvres and experience, which users belonging to different ages and gender groups possess varyingly. The interaction between the cyclist and the road environment is physically intensive compared with the motorists who benefit from a secure machine at their disposal. The resulting physical and cognitive strains from different infrastructures result in statistically significant safety variation for riders belonging to different age and gender groups.

6.4. Deep learning neural model

A deep learning model is constructed with a neural network classifier and backpropagation error function. The model predicts the riskiest age and gender group based on specific spatial, environmental and infrastructure input variables. There are six deep learning models constructed, whose accuracy is estimated by evaluating their distinguishable power between the riskiest and non-riskiest age and gender group through AUROC, presented in Table 6.7 and Fig 6.3.

Table 6.7. The area under the curve for the three constructed deep learning models

	Spatial		Environment		Infrastructure	
	M	F	M	F	M	F
under 17	0.91	0.94	0.61	0.68	0.87	0.94
17-24	0.93	0.98	0.56	0.72	0.87	0.95
25-34	0.93	0.98	0.57	0.7	0.90	0.96
35-44	0.92	0.92	0.56	0.58	0.89	0.93
45-54	0.9	1.00	0.62	0.85	0.86	0.96
55-64	0.95	0.92	0.71	0.82	0.93	0.96
over 65	0.94	0.97	0.58	0.61	0.87	0.94
Total	6.47	6.71	4.21	4.96	6.19	6.64
Average	0.92	0.96	0.60	0.71	0.88	0.95

high (100%) low (55%)

where *M* = Male, and *F* = Female

Significantly high accuracy is obtained in all the constructed models, with an average AUROC value of 84%. There are seven output values that each model can take. Therefore, ideally, for a 100 % accuracy, the maximum value of AUROC, that can be achieved is seven. The AUROC values obtained for male (female) are,

i) Spatial: 6.47(6.71),

ii) Infrastructure variables 6.19 (6.64), and

iii) Environment: 4.21 (4.96).

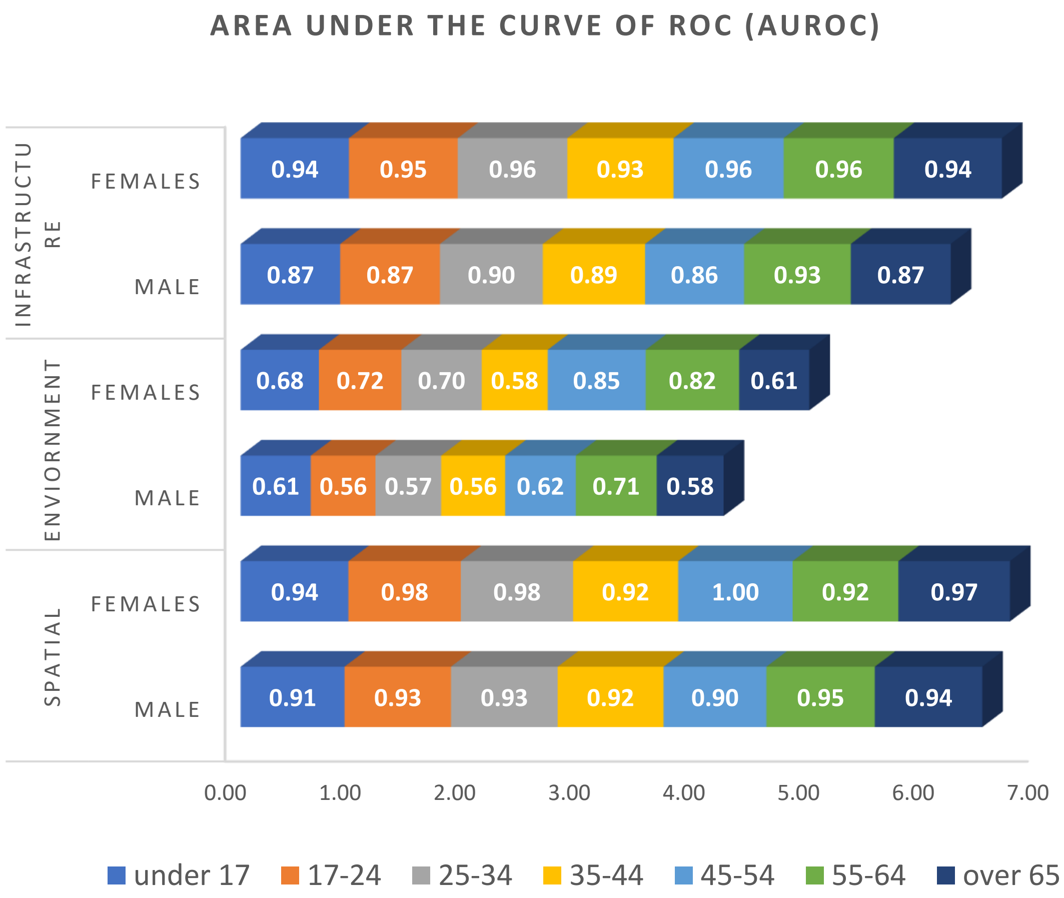


Figure 6.3. Area under the curve of the receiver operator characteristics curves for the constructed models

These values indicate a high predictive distinguishable power. The environmental conditions are a significant mode choice variable (see (Heinen, Maat and Van Wee, 2011)); hence, the safety model, without considering the mode choice variability as expected, will result in a comparatively less predictive model. The cyclist is susceptible to change their mode due to changes in the prevailing condition. However, the accuracy achieved even for this least accurate model is higher than what is commonly available in the literature and used by road safety professionals (see (Yannis *et al.*, 2015)). It can also be deduced that a particular cyclist is more susceptible to the spatial and infrastructure variables, having a varying effect on the safety for a particular cyclist based upon its personal attribute. The adverse environmental conditions are expected to decrease all the users' safety; however, the risk level varies for different groups. The spatial variables are a representation of the traffic flow regime and journey purpose, resulting in a higher level of physical and cognitive strains. The infrastructure variables demonstrate a similar phenomenon as the physical and cognitive abilities of the riders belonging to a different age, and gender group is different. Therefore, the safety implications are also varied, making it possible to predict the riskiest age and gender group based upon the specific input variables. The most accurate predictive model is the model constructed using spatial variables, which is explained explicitly through its network topography (Fig 6.4) ROC curve's (Fig 6.5), gain (Fig 6.6), and lift (Fig 6.7) charts (detailed infrastructure and environment models are attached in the appendices).

The ROC curve line for all the variable cases is closer to the upper left corner, farther away from the 45^0 basslines, which depicts significantly high prediction capability, evident from the AUC values. The gain is a measure of the constructed model's effectiveness calculated as the percentage of the correct predictions obtained within the model versus the accurate predictions obtained without the model, i.e., baseline. A significant higher gain is obtained for the output 55-64 female age group (10%, 100%), i.e., if wrong predictions are sorted by their pseudo probabilities, the top 10% of the dataset will have all the 100% cases of improper predictions. Similarly, from the gain chart, the gain value for the 55-64 female group, at 10% data, is 10, i.e., the accuracy of the model is ten times higher than the base case at this point.

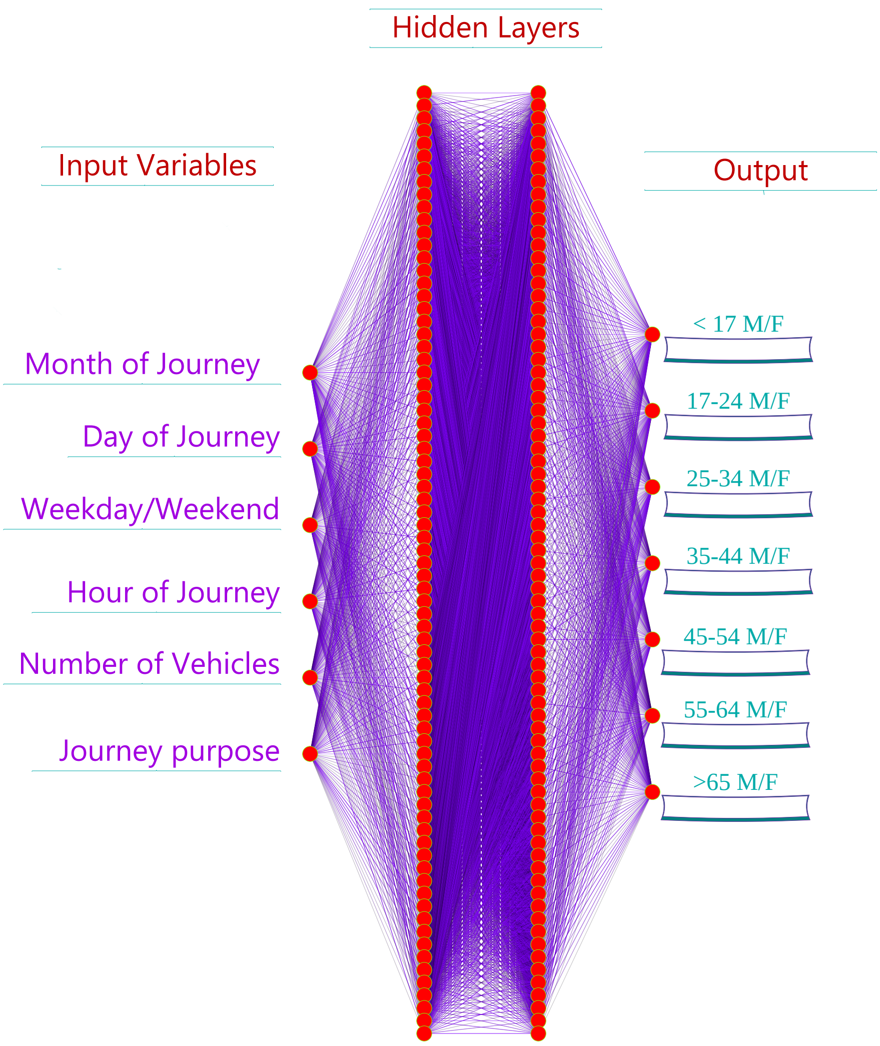


Figure 6.4. Network topography of the spatial variable model

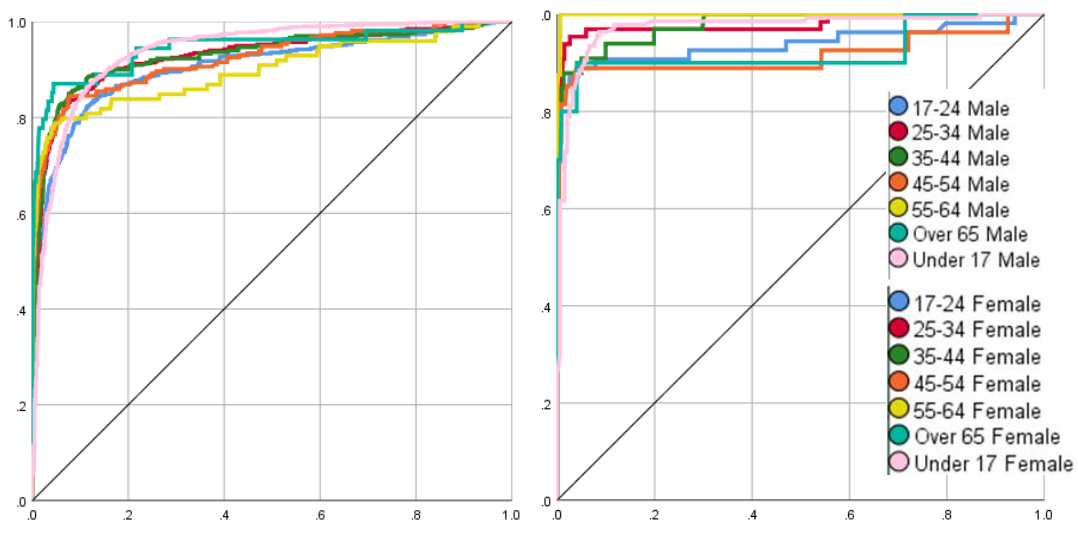
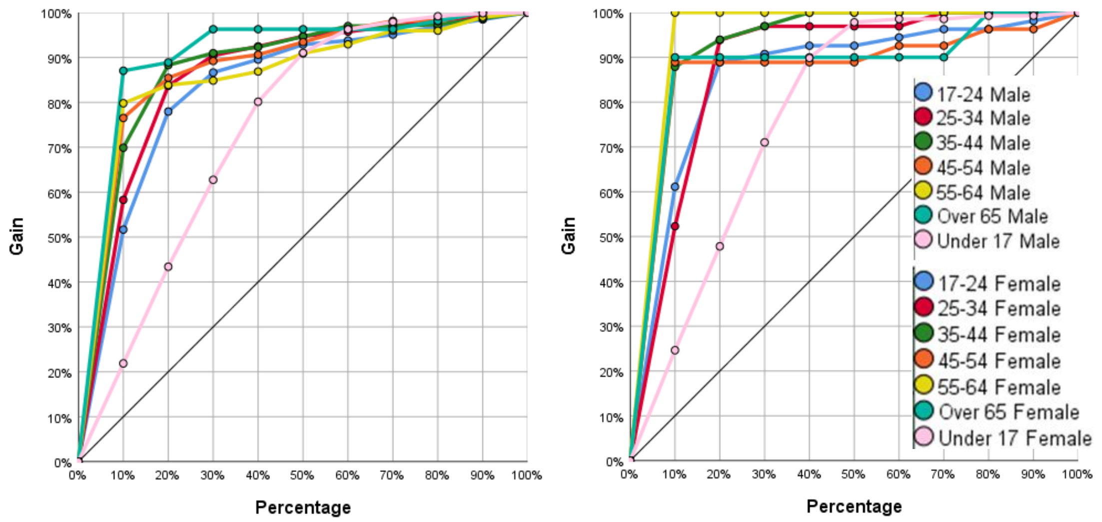
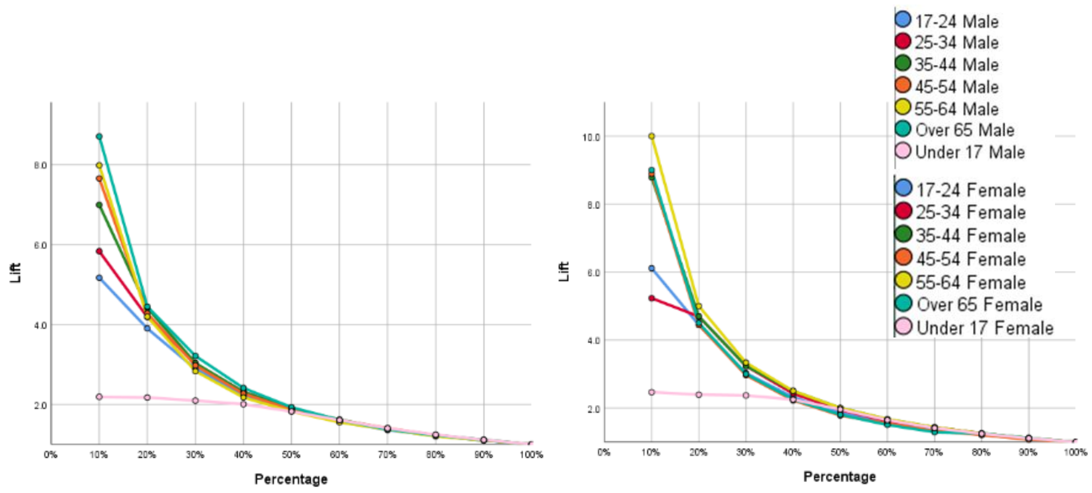


Figure 6.5. Receiver Operating Characteristics (ROC) curve a) Male, and b) Female



a) b)

Figure 6.6. Gain chart a) Male, and b) Female



a) b)

Figure 6.7. Lift chart a) Male, and b) Female

6.5. Critical variable significance

6.5.1. Variable importance

The data learning model's critical variables are identified through the variable, and normalised significance (Table 6.8), based upon both testing and validation data sets.

Table 6.8. Normalised importance of various variables in the three constructed models

		Male		Female	
		I	N_I	I	N_I
Spatial	Month	0.170	73.8	0.192	90.3
	Day	0.143	62.3	0.165	77.6
	Weekday or Weekend	0.101	43.9	0.111	52.4
	Hour	0.201	87.6	0.212	100.0
	Number of Vehicles	0.156	67.7	0.172	81.1
	Journey Purpose of Driver/Rider	0.230	100.0	0.149	70.0
Infrastructure	Road Type	0.081	83.3	0.071	81.7
	Speed Limit	0.076	77.6	0.069	79.1
	1st Road Class	0.074	75.4	0.067	77.2
	Road Hierarchy level	0.075	77.1	0.065	74.4
	Road Hierarchy level direction	0.098	100.0	0.083	95.2
	Junction Detail	0.092	94.5	0.080	91.8
	Junction Control	0.079	80.7	0.066	76.1
	2nd Road Class	0.082	84.5	0.070	80.9
	Vehicle Manoeuvre	0.096	98.2	0.087	100.0
	Road Location of Vehicle	0.086	88.4	0.072	82.3
	Junction Location of Vehicle	0.094	96.8	0.067	76.6
	Skidding and Overturning	0.067	68.4	0.069	79.9
Environment	Light Conditions	0.341	93.9	0.422	100.0
	Weather	0.363	100.0	0.344	81.6
	Road Surface Condition	0.296	81.6	0.234	55.5

where I = Importance, and N_I = Normalised Importance in percentage.

The most critical variable for female riders is the journey hour, whereas it is the journey purpose for males in the spatial model. The journey hour represents a combination of variables, i.e., traffic flow regime and lighting condition. Women have been reported in the literature to be significantly susceptible to these externalities. Also, motorists are reported to exhibit behaviour sensitivities toward the gender appearance of the cyclists (see (Walker, 2007)), which further complicates the cyclists-motorist interaction. However, for men, their journey purpose is the critical variable representing the behavioural nature, an expected variable from traditional road safety theory. Hence, it could be inferred that women cyclists are more susceptible to varying traffic flow conditions than male cyclists.

The normalised importance values do not differ significantly in the infrastructure model compared with the other two models. This leads us to infer that the overall effect of micro infrastructure variables is not significantly different for riders belonging to a different gender. However, these critical variables vary and differ by a small proportion in the rank of importance. For females (males), the most critical variables are vehicle manoeuvre (road hierarchy level and direction), followed by road hierarchy level and direction (vehicle manoeuvre), junction details (junction location of the vehicle), road location of the vehicle (junction detail), and road type (road location of the vehicle). The rest of the variables' importance rank is similar; however, their normalised importance values vary slightly. This leads us to conclude that specific attributes of the infrastructure are risky for all cyclists. However, the level of risk which each infrastructure attribute possesses is dependent upon the gender of the rider. The results agree with the findings in the literature. The infrastructural hazards present different levels of risk to the cyclist based upon its gender (see (Abdel-Aty and Radwan, 2000; Aldred, Woodcock and Goodman, 2016)), and that a bad infrastructure design/ condition is rated poorly by the cyclists irrespective of its gender (see (TRL, 2011)). The novel variable introduced in the study, i.e., road hierarchy level and direction, is significant, and it is recommended that this variable be considered in the cyclists' road safety investigations. The sudden change in the road hierarchy requires a shift in how the cyclists need to interact with the infrastructure and other road users. The direction of change, i.e., whether the hierarchy's change is from a low class of road to a higher level or vice-versa, is a critical externality.

In the environmental variable model, critical variable for females are lighting (100%), meteorological (82%), and road surface condition (56%); whereas for males, it is meteorological (100%), lighting (94%), and road surface condition (82%). Therefore, we can conclude that environmental conditions have a significantly different impact on safety depending upon the gender of the trip maker. The lighting and meteorological conditions are hazards perceived differently by females. From the spatial model, the hour of the journey (88% for males and 100 % for females) is a critical variable representing the flow regime and lighting conditions. This is validated by the environment model in which lightings conditions is the most critical variable for female riders. This leads to conclude that the lighting condition adversely affects cyclists' safety with a much more profound effect on females. The few findings from this study have been reported in the literature; however, these have not been mathematically validated or their impact quantified.

6.5.3. Statistical validation

The association between the target variable and input variables is tested statistically using the chi-square test (Table 6.9), and their association is quantified through the Cramer V value (Table 6.10).

Table 6.9. Chi-square test for testing association between input variables and rider gender

H_0 H_1	Male			Female		
	χ^2	p-value	H_A	χ^2	p-value	H_A
Month	167.6	0.01	H_1	195.21	0.01	H_1
Day	91.8	0.01	H_1	110.2	0.01	H_1
Weekday/Weekend	12.0	0.045	H_0	11.98	0.062	H_0
Hour of Journey	610.0	0.01	H_1	27.64	0.01	H_1
Journey Purpose.	480.3	0.01	H_1	86.16	0.01	H_1
Number of Vehicles.	215.0	0.01	H_1	43.37	0.01	H_1
Road Type.	154.3	0.01	H_1	100.68	0.01	H_1
Speed Limit.	246.1	0.01	H_1	55.98	0.01	H_1
1st Road Class	348.0	0.01	H_1	56.77	0.01	H_1
Junction Detail	225.4	0.01	H_1	92.73	0.01	H_1
Junction Control	52.3	0.01	H_1	50.81	0.01	H_1
2nd Road Class	175.3	0.01	H_1	110.97	0.01	H_1
Road Hierarchy Level	135.7	0.01	H_1	35.69	0.06	H_0
Road Hierarchy Level and Direction	203.0	0.01	H_1	69.3	0.02	H_1
Vehicle Manoeuvre.	321.1	0.01	H_1	95.172	0.01	H_1
Skidding and Overturning	56.7	0.01	H_1	66.67	0.01	H_1
Road Location of Vehicle	170.0	0.01	H_1	106.74	0.01	H_1
Junction Location of Vehicle	191.9	0.01	H_1	79.24	0.01	H_1
Light Conditions	203.8	0.01	H_1	70.43	0.01	H_1
Meteorological Conditions (Weather)	71.2	0.016	H_1	45.37	0.25	H_1

Road Surface Condition	*84.1*	*0.01*	H_1	*41.48*	*0.01*	H_1

where H_0 = Null hypothesis, i.e., the risk for a rider belonging to a particular age and gender is independent of the variable, H_1 = Alternate hypothesis, i.e., the risk for a rider belonging to a particular age and gender is dependent on the variable, χ^2 = Pearson chi-square value, and H_A = Hypothesis adopted.

Table 6.10. Cramer V value and type of association for different variables across gender

Variable	Male		Female	
	V	A_T	V	A_T
Month	0.10	S	0.30	L
Day	0.07	S	0.23	L
Weekday/Weekend		n/o		n/o
Hour of Journey	0.18	M	0.36	L
Journey Purpose.	0.18	M	0.25	L
Number of Vehicles.	0.14	S	0.25	M
Road Type.	0.10	S	0.27	L
Speed Limit.	0.13	M	0.20	M
1st Road Class	0.17	M	0.20	M
Junction Detail	0.11	S	0.21	M
Junction Control	0.08	S	0.22	M
2^{nd} Road Class	0.11	S	0.25	L
Road Hierarchy Level	0.11	S		n/o
Road Hierarchy Level and Direction	0.11	S	0.18	M
Vehicle Manoeuvre.	0.14	M	0.21	M
Skidding and Overturning	0.08	S	0.25	M
Road Location of Vehicle	0.10	S	0.24	L

Junction Location of Vehicle	0.11	S	0.19	M
Light Conditions	0.11	S	0.18	M
Meteorological Conditions (Weather)	0.06	S	0.18	M
Road Surface Condition	0.10	S	0.24	M

where *V* = Cramer V value, A_T = Type of Association, *S* = Small, *M* = Medium ,*L* = Large, and *n/o* = no association

In the chi-square test, all the variables except weekday/weekend and road hierarchy level (for females only) are statistically associated with the gender of the trip maker at a 99.9% confidence interval. The level of association is quantified through Cramer V and Cohem table. For males, a medium level of association is obtained for the hour of journey, speed limit, first road class and vehicle manoeuvre. A small level of association is obtained for all the other variables (except weekday/weekend). Females have a high level of association for the month, day, hour, journey purpose, road type, and rider road location. A medium level of association is obtained for all the other variables, except the weekday/weekend and road hierarchy level. The association between the input variables and gender is significantly different for each variable, reinforcing its validation as a dynamic input variable. These results validate the deep learning results; the least important variable in the spatial model is weekday/weekend across gender. In the infrastructure model for females, the least essential variable is the road hierarchy level. There is no association found for these two variables. Furthermore, according to the deep learning model, females are more susceptible to varying traffic flow conditions, as illustrated by their high association level. The month, day, and hour of the journey represent the traffic flow regime plying during the crash.

6.6. Logistic regression

In the logistic regression model, the gender of the cyclist is used as the response variable. Only the significant variable models are presented. The results from the multiple regression model are presented in Table 6.11 and Equation 6.1.

Table 6.11. Multiple logistic regression model for the gender response variable

	Coefficient	p-value	*OR*	95% *C.I* for *OR*	
				L_L	U_L
Hourly flow rate (x_1)	-0.14	0.01	0.87	0.78	0.97
Traffic flow regime (x_2)	0.65	0.00	1.91	1.35	2.71
Peak (x_3)	-0.87	0.01	0.42	0.23	0.78
Lighting conditions (x_4)	-0.60	0.00	0.55	0.36	0.83
Weather (x_5)	0.62	0.03	1.86	1.06	3.27
Meteorological Road Surface condition (x_6)	0.48	0.04	1.62	1.02	2.56
Driver Age Group		0.06			
Driver Age Group 1 (17-24)	0.22	0.19	1.24	0.90	1.72
Driver Age Group 2 (25-34)	0.43	0.01	1.54	1.13	2.10
Driver Age Group 3 (35-44)	0.00	1.00	1.00	0.67	1.49
Driver Age Group 4 (1)	0.15	0.51	1.16	0.75	1.78
Driver Age Group 5 (5-64)	-0.36	0.34	0.70	0.33	1.47
Driver Age Group 6 (over 65)	0.59	0.09	1.80	0.92	3.56
Constant	-2.36	0	0.09		

where OR = Odds ratio, and C.I = confidence interval, L_L = Lower limit, and U_L = Upper limit.

Through logistic modelling, the following variables (odds ratio) emerge as statistically significant at a 95% confidence level:

i) Hourly flow rate (0.87),

ii) Traffic flow regime (1.91),

iii) Whether the journey is being made in peak hour (0.42),

iv) Lighting conditions (0.55),

v) Weather (1.86), and

vi) Meteorological road surface conditions (1.62).

The variable age is not statistically associated with the gender of the rider. The modelling results in the final statistical equation, presented in Eq 6.1.

$$Logit(p) = \ln\frac{p}{1-p} = -a_0 - a_1x_1 + a_2x_2 - a_3x_3 - a_4x_4 + a_5x_5 + a_6x_6 \quad (6.1)$$

where x_1 = Hourly flow rate, x_2 = Traffic flow regime, x_3 = Peak, x_4 = Lighting conditions, x_5 = Weather, and x_6 = Meteorological Road Surface condition.

The estimated coefficient values $a_0, a_{1,}, a_2, a_3, a_4, a_5,$ and a_6 values are 2.36, 0.14, 0.65, 0.87, 0.6, 0.62, and 0.48, respectively.

$$p = \frac{e^{logit(p)}}{1 + e^{logit(p)}} \quad (6.2)$$

where $p =$ probability of female crashes, $1 - p =$ pobability of male crashes

Some interesting results are obtained; a unit increase in the hourly traffic flow results in a relative increase in male cyclist risk by 1.15 times (1/0.87 = 1.15). Similarly, males' relative risks increase by 2.38 times (1/0.42 = 2.38) during the peak hours compared with the non-peak hour. The traffic flow regime is modelled as 0 = overnight flow, 1 = day flow, 2 = morning peak flow, 3 = evening peak flow. The traffic flow regime has a positive association, implying that female riders relative risks increase with the evening peak within the overall peak.

The lighting conditions as modelled as 0 for daylight and 1 for darkness. The male crash probability increases by 1.82 (1/0.55) times as the lighting conditions change from daylight to darkness. However, as both weather conditions and meteorological road conditions change from fine (dry) to wet (damp), the probability for female crashes increase by 1.86 and 1.82 times, respectively. Thereby, leading to conclude that the meteorological conditions present a higher risk to females compared with males. The temporal and spatial variance in the journey for men and women is widely acknowledged in the literature (see Beecham, 2013, Aldred, Woodcock and Goodman, 2016) . Women rarely prefer to travel in high traffic (motorized) flow and have been reported to alter their journeys to avoid former and prefer quiet streets with low traffic. A similar statistically significant relationship is obtained in the study for the reported crashes. Also, as the traffic flow increases, there is a relative increase in cyclist safety through a reported Safety in Numbers phenomenon (SiN). Therefore, it can be inferred that female rider is more susceptible to SiN compared with males. Future research should aim to develop a mode and route choice model simultaneously for cyclists based upon their personal attributes of age and gender and then compare the safety and said models. The work presented in this study is the first step towards developing an in-depth understanding of the variation of cycling safety with the dynamic variables.

6.7. Chapter Summary

In this chapter, the influence of the gender attribute of the cyclist concerning cycling safety is modelled. An intelligent hybrid framework consisting of risk rates, normalised risk, heat maps, ANOVA, post-hoc comparison, deep learning neural network, chi-square, Cramer V, and logistic regression is developed. Six accurate prediction models are developed, and an understanding of critical variables affecting a rider's safety is achieved. It is shown that the men overall ride more recklessly than women. Hence, a focus on men training should be explored. The infrastructure planning and design should also vary based upon the demographics of a particular urban area, rather than a generalized approach at a macro level, such as a country. The spatial and environmental variables have a significantly varied effect on safety depending upon the gender of the rider interacting with the infrastructure. Men are susceptible to their journey purpose, meteorological conditions, whereas females are more susceptible to externalities such as traffic flow regime. Similarly, lighting conditions have a more pronounced impact on females. There are certain features of the infrastructure that are risky for all cyclists. However, the level of risk that each infrastructure variable presents is dependent upon the rider gender. An increase in the hourly flow rate for the journey during the peak results in a relative increase in the risk for a male rider. The female rider benefits more from the Safety in Numbers (SiN) phenomenon. Similarly, adverse meteorological conditions present a higher level of risk to females.

The intricacies reported in this research will be lost if any attempt is made to undertake a generalised road safety investigation across age and gender. The results reinforce the need to design the infrastructure for intended users rather than overall infrastructure usage at an aggregate level, such as the state or country level. The recommended modelling at the nanoscopic level can be aggregated for safety investigation of the entire area under study, rather than the contrary approach presently used. Such an approach will improve modelling capabilities and better understand cycling safety in their natural urban environment.

Chapter 7.

Modelling variable environmental conditions to derive their cycling safety implications

7.1. Introduction

In addition to age and gender, a cyclist manner of interaction with the road infrastructure also depends upon the variable environmental conditions of lighting and meteorological road surface. This chapter is concerned with nanoscopic rider safety modelling by considering variable environmental conditions. There are very few works in the literature dealing with such modelling. The literature has widely reported that extended periods of rainfall negatively affect cycling, affecting the selection of cycling as a mode of travel and its safe usage of infrastructure (Sabir *et al.*, 2009). The English and Wales mode choice model (Parkin, Wardman and Page, 2008) reported that rainfall has high negative cyclist flow elasticity. The variable environment conditions can result in an additional variable for the cyclist to deal/ negotiate with while interacting with the infrastructure under different traffic flow regimes, thereby acting as a significant hazard. This phenomenon can be attributed to the safety law of complexity (Elvik, 2006); which states, more the variables road user has to attend to; notable is the risk faced. The rain degrades the driving environment due to several physical factors: a possible loss of friction between the tyre and road, impaired visibility, and a spray of water from other vehicles (Jaroszweski and McNamara, 2014). These conditions can also impact the cyclist cognitive capability (safety law of cognitive capacity), making it a potential safety hotspot. However, during adverse environmental conditions, only full-time committed cyclists are reported to use the infrastructure. These have better skills and are better equipped to negotiate the infrastructure. Also, in the literature, it has been postulated that such adverse conditions can result in a relative increase in safety, as both riders and drivers are extra careful during such conditions. Most of the studies have focussed on the perceived safety, rather than real safety, and very few results have been mathematically validated. To develop a knowledge driven approach, a better understanding of this phenomenon is required, with the results mathematically validated. The effect of varied environment on safety can have different implications for a cyclist varying from one rider to another (Heinen, Maat and van Wee, 2011).

It was established in Chapter 2 that in the literature, there is an *"Absence of an accurate and dynamic model for cyclists, which can model varied environmental conditions"*. This chapter seeks to improve the understanding of how environmental conditions affect road safety for a particular rider. Hence, the aim is to develop a road safety model for a cyclist at the individual level (nanoscopic), predict the environmental conditions most likely to be unsafe based on the specific input variables, and investigate the causal relationship between the input variables and riskiest environment condition. More precisely, our objectives are to:

- Investigate, and develop an understanding of how cyclist's safety varies with varying environmental conditions.

- Test the hypothesis that the unsafeness of interaction between rider and infrastructure depends on the lighting and meteorological road surface condition.

- Develop a nanoscopic road safety model with the environmental condition as the output.

- Identify the most critical variable affecting the unsafeness during a prevalent environmental condition for an individual rider.

- Develop an understanding of how different variables affect safety during varied environmental conditions.

7.2. Traditional statistical Model and heatmap

The traditional statistical model, comprising of crash rates, is presented in Table 7.1 and Table 7.2. There are 3,325 (79.3% slight, 19.9% serious, and 0.8% fatal) cyclist crashes reported in the study area. Out of these, 83 % occurred in daylight and 82% on the dry road surface. It is established from the literature (Heinen, Maat and van Wee, 2011) that cyclist mode choice is highly varied and susceptible to change due to change in environmental conditions. As the mode usage during these adverse conditions is low, reported crashes are also low. There is a strong bias towards daylight crashes. This has the potential to result in modelling inaccuracy in the predictive deep learning model, as it will be difficult for the neural network to learn, classify and test effectively, and distinguish between different output variables. Therefore, lighting variables are further grouped into another environmental variable, i.e., meteorological road surface condition (Table 7.2). Most crashes (72%) occur in daylight lighting conditions and dry meteorological road surface conditions. This division ensures a relatively lower bias, thereby providing a better opportunity for the neural network to learn and predict accurately.

Table 7.1. Crash classification by a) severity b) varying environmental conditions in the study area

Variable	*f*	Variable	*f*
Slight	2638	Darkness	542(16.8%)
Serious	661	Daylight	2683 (83.2%)
Fatal	26	Dry	2644 (82%)
Total	3325	Wet/Frost/Snow	581(18%)

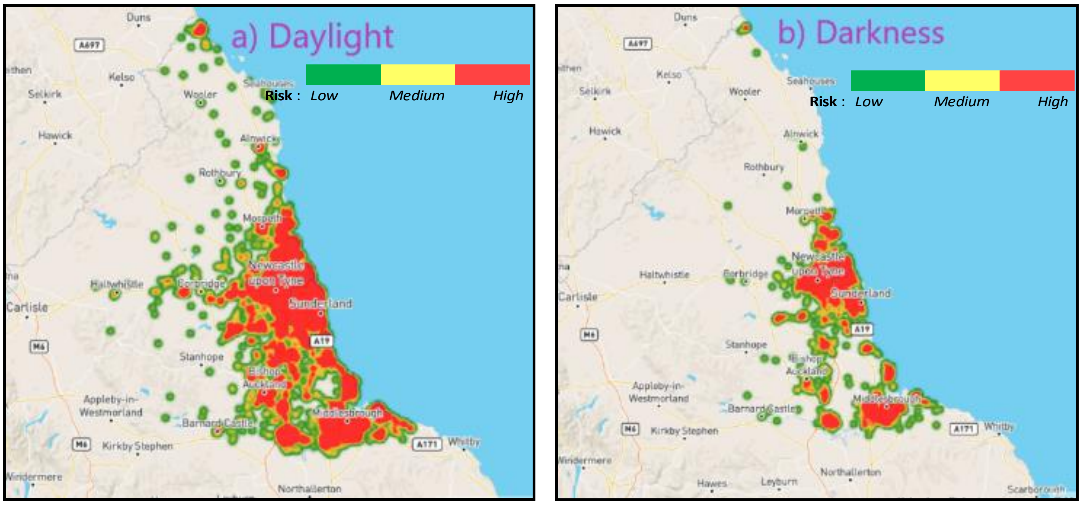
where *f* is the frequency

Table 7.2. Crash variation with varying environmental conditions of lighting and meteorological road surface conditions

Variable	*f*	%age	Variable	*f*	%age
Darkness - No Street Lighting, and Dry	25	0.8	Darkness - Street Lights present, unlit and Dry	*8*	*0.2*
Darkness - No Street Lighting, and Wet/Damp	23	0.7	Darkness - Street Lights present, unlit and Wet/Damp	*1*	*0*
Darkness - Street Lighting Unknown, and Dry	10	0.3	Daylight and Dry	*23 33*	*72.3*
Darkness - Street Lighting Unknown, and Wet/Damp	4	0.1	Daylight and Frost	*16*	*0.5*
Darkness - Street Lights present, lit and Dry	26 8	8.3	Daylight and Snow	*1*	*0*
Darkness - Street Lights present, lit and Snow	6	0.2	Daylight and Wet/Damp	*33 3*	*10.3*
Darkness - Street Lights present, lit and Wet/Damp	19 7	6.1	*n/a*	*n/ a*	*n/a*

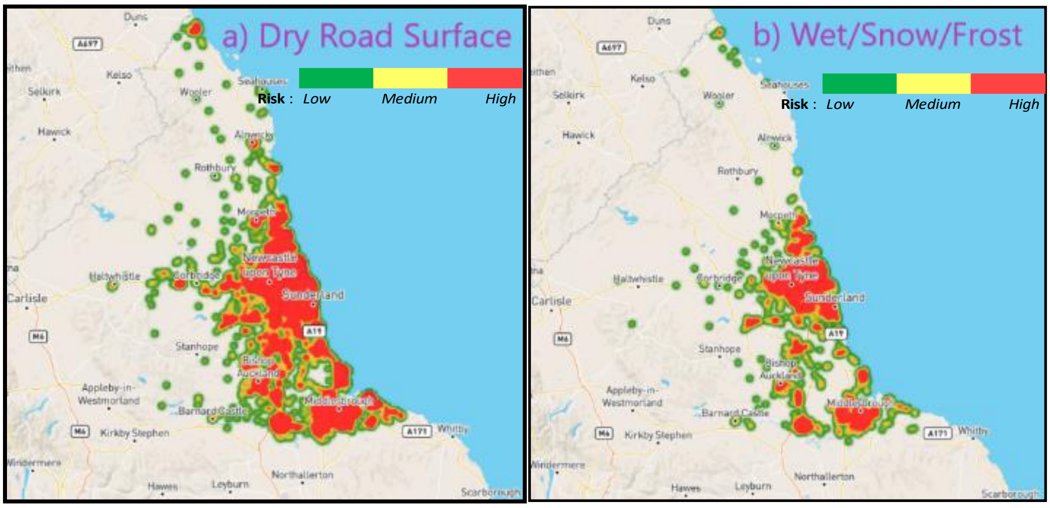
where *f* is the frequency

The results suggest that most crashes occur in daylight and on dry meteorological road surface conditions. The results may lead to infer that these environmental conditions are riskier for cyclists. However, it is already established in the literature that the cycling mode share is highly varied and can change daily and on an hourly basis (Heinen, Maat and van Wee, 2011). As the mode usage varies during the adverse conditions, concluding without considering the mode usage is improper. The parking is freely accessible across the study area for a cyclist. In the generalised cost modelling, the parking impedance is zero for both route and mode choice. During adverse environmental conditions, the cycle can be parked at a suitable place overnight for free. Hence mode usage during adverse conditions is relatively low. Nevertheless, experienced cyclists continue to use the mode during these uncongenial environment externalities. It is imperative to understand the spatial variation of crashes for different conditions of: a) Daylight and Darkness (Fig 7.1), b) Dry and Wet meteorological road surface conditions (Fig 7.2), and c) Daylight and dry, darkness and wet (Fig 7.3). The following risk heatmaps are generated for these three different scenarios.



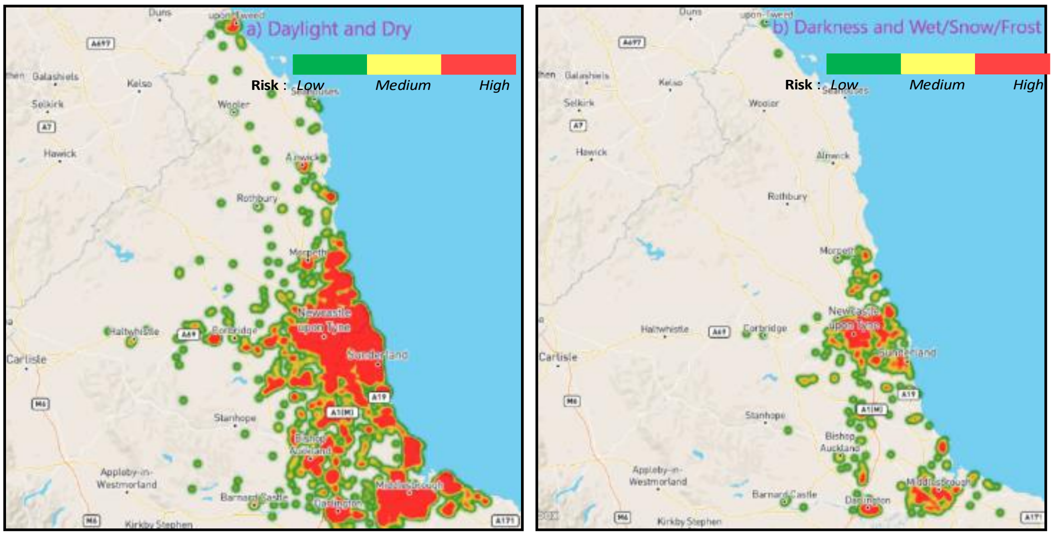
a) b)

Figure 7.1. Risk heatmaps for hotspot identification for a) Daylight and b) Darkness



a) b)

Figure 7.2. Risk heatmaps for hotspot identification for a) Dry meteorological road surface condition, and b) Wet/Snow/Frost



a) b)

Figure 7.3. Risk heatmaps for hotspot identification for a) Daylight and dry meteorological road surface condition, and b) Darkness and Wet/Snow/Frost

The results from risk heatmaps suggest how different locations act as a hotspot, depends upon the lighting and meteorological road surface condition variables. The patterns and spread of crashes are significantly different for each environmental variable, except for the expected centralisation in Newcastle city centre. This leads to conclude that the safe usage of infrastructure depends on the environmental conditions that a rider is subjected to, with varying risks for:

i) Daylight and darkness,

ii) Dry, and wet/snow/frost road surface, and

iii) Daylight with dry and darkness with wet/ snow/frost meteorological road surface condition.

These conditions result in a varied level of risk for the same type of infrastructure to the cyclist, making the rider's subjected environmental conditions a dynamic road safety variable. The heatmaps also validate the earlier assumption of combining the two environmental variables of lighting and meteorological road surface conditions, as both these variables are found to individually and combined, affect different infrastructures' safety variedly.

This is an unexpected finding, contrary to the traditional road safety models/theories from the literature. Although acknowledging that road infrastructure and safety are interlinked; however, the present models do not consider that the environmental conditions may affect divergent infrastructures' safety differently. This reinforces the Dublin cycling model (Lawson, 2015) conclusion that the present models do not consider the cyclist limitations and vulnerability. Unlike cyclists, the motorists are not significantly affected by these adverse environmental conditions, e.g., wet road surface conditions will only affect the friction and skid resistance for the motorists. This effect is usually the same across all types of infrastructure. However, for a cyclist, the interaction with the infrastructure is already much more complicated and difficult. The safety genesis for different infrastructures is significantly different. These adverse conditions pose varying challenges for the rider while using the infrastructure, which results in both physical and cognitive strains, thereby, acting as a significant road safety variable (safety law of cognitive capability (Elvik, 2006)). This leads to postulate that complex environmental conditions of lighting and meteorological road surface condition, alone and in combination, affect the cyclist's safe interaction with infrastructure. This variable needs to be modelled effectively and efficiently to develop the requisite knowledge-driven approach for cycling infrastructure. Such modelling will enable creating a dynamic safety index, which will allow for safety analysis at the individual (nanoscopic) rather than the macroscopic level. This shift in safety analysis towards nanoscopic modelling can help achieve the zero-vision road traffic fatality demonstrated in the corresponding sections.

7.3. Deep learning model

There are three deep learning models constructed with neural network classifier and backpropagation error function. The model predicts the output of the riskiest environmental conditions of lighting and meteorological conditions based on specific spatial, personal, and environmental variables. As the output has a strong bias towards the daylight and dry crashes, a highly non-linear structure comprising two hidden layers, with each layer having 350 units, is used for model development; the principal characteristics are described in Table 7.3.

The accuracy of the constructed models is evaluated through their ROC curves (Fig 7.4). The AUROC values are used for numerical quantification of accuracy, presented in Table 7.4. In addition to the average AUROC values, the AUROC values of each output variable are evaluated. This ensures that both overall model accuracy and individual variable accuracy are gauged. Deep learning is a complex advanced machine learning methodology whose application needs to be evaluated compared with the probability-based statistical model. This is undertaken through the development of the lift charts (Fig 7.5).

Table 7.3. Characteristics and structure of the constructed network

Input Layer		Spatial model	Personal Model	Infrastructure model
	1	Hour	Gender	Road Type
	2	Number of Vehicles	Age	Speed limit
	3	Month	Age and Gender (combined)	1st Road Class
	4	Day	Journey Purpose	Road Hierarchy Level
	5	Weekday or Weekend	n/a	Road Hierarchy level and direction
	6	n/a	n/a	Junction Detail
	7.	n/a	n/a	Junction Control
	8	n/a	n/a	2nd Road Class
	9	n/a	n/a	Vehicle Maneuver
	10	n/a	n/a	Vehicle Junction Location
	11	n/a	n/a	Road Location of vehicle
	12	n/a	n/a	Carriageway Hazards
	No. of Input Units	50/ 29/86		
Hidden Layer(s)	Total No. of Hidden Layers	2		
	Total No. of Units in the Hidden Layers	700 (350in each layer)		
Output Layer	Dependent Variables	Riskiest Environment Condition		
	Total No. of Output units	13		
	Error Function	Cross-entropy		
Activation Function for Hidden Layers		Hyperbolic tangent		
Activation Function for Output Layer		SoftMax		

Table 7.4. The area under the curve of ROC for three constructed deep learning models

	Spatial	Personal	Infrastructure	Average
Darkness - No Street Lighting, and Dry	0.94	0.74	0.87	0.85
Darkness - No Street Lighting, and Wet/Damp	0.92	0.81	0.97	0.9
Darkness - Street Lighting Unknown, and Dry	0.7	0.88	0.96	0.85
Darkness - Street Lighting Unknown, and Wet/Damp	1	0.94	0.82	0.92
Darkness - Street Lights present, lit and Dry	0.98	0.67	0.86	0.84
Darkness - Street Lights present, lit and Snow	1	0.97	1	0.99
Darkness - Street Lights present, lit and Wet/Damp	0.99	0.75	0.87	0.87
Darkness - Street Lights present, unlit and Dry	0.98	0.66	0.87	0.84
Darkness - Street Lights present, unlit and Wet/Damp	1	0.85	0.42	0.76
Daylight and Dry	0.96	0.64	0.84	0.81
Daylight and Frost	0.96	0.91	0.87	0.91
Daylight and Snow	1	0.79	0.9	0.9
Daylight and Wet/Damp	0.92	0.63	0.86	0.8
Total	12.36	10.22	11.11	11.23
Average	0.95	0.79	0.85	0.86

high low

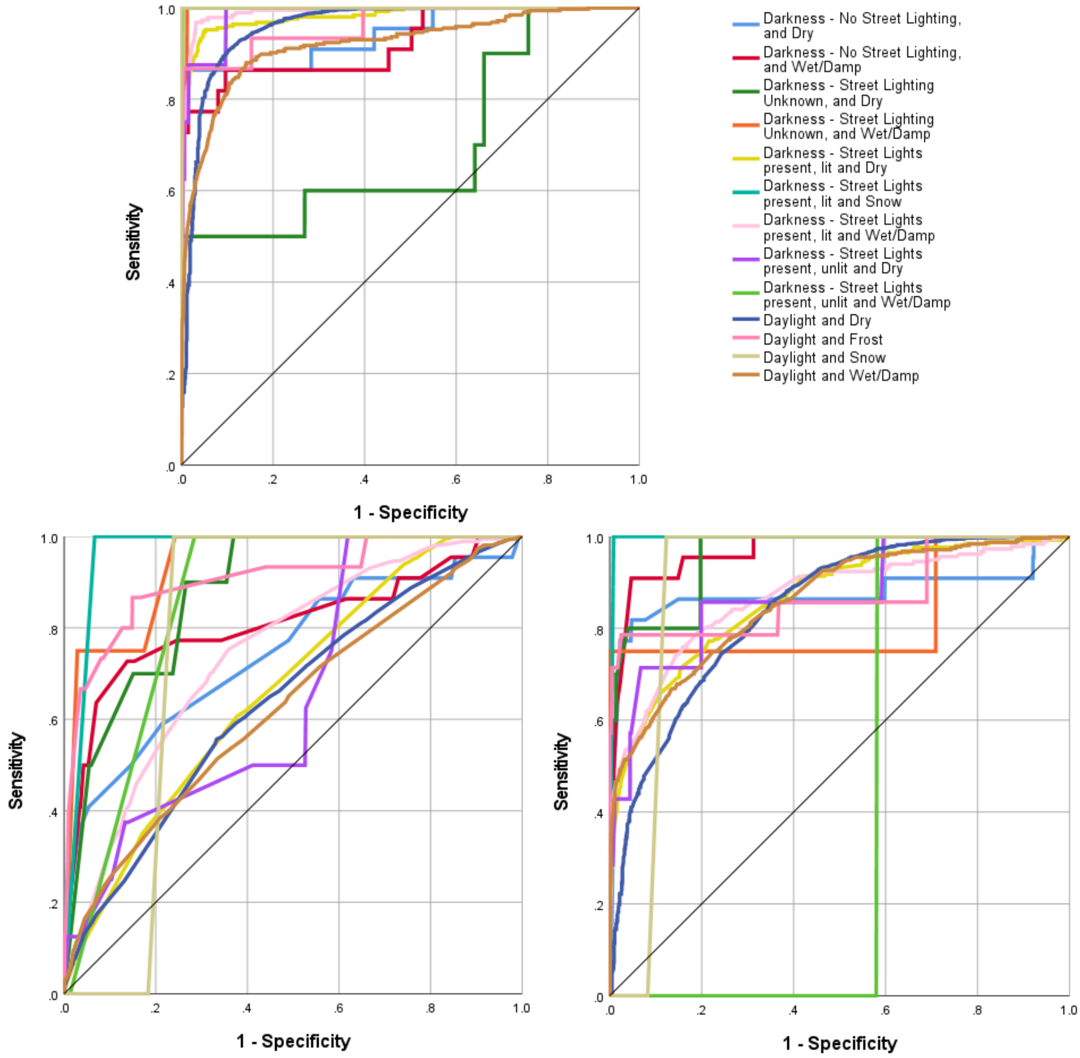
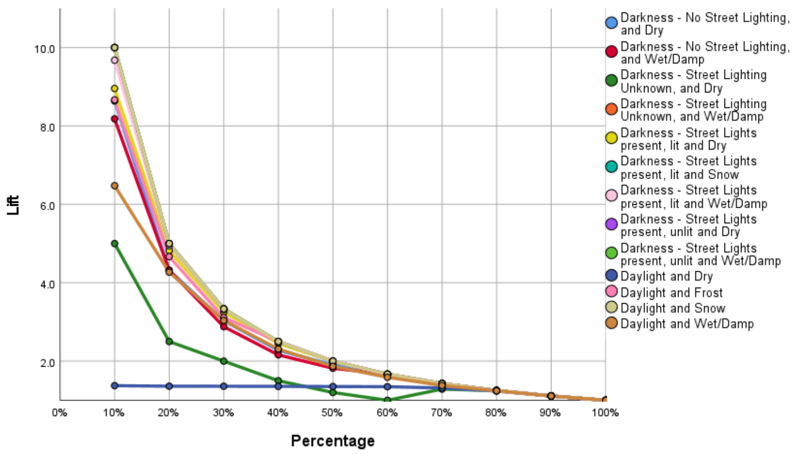


Figure 7.4. Receiver Operating Characteristics (ROC) curve a) Spatial, b) Personal, and c) Infrastructure



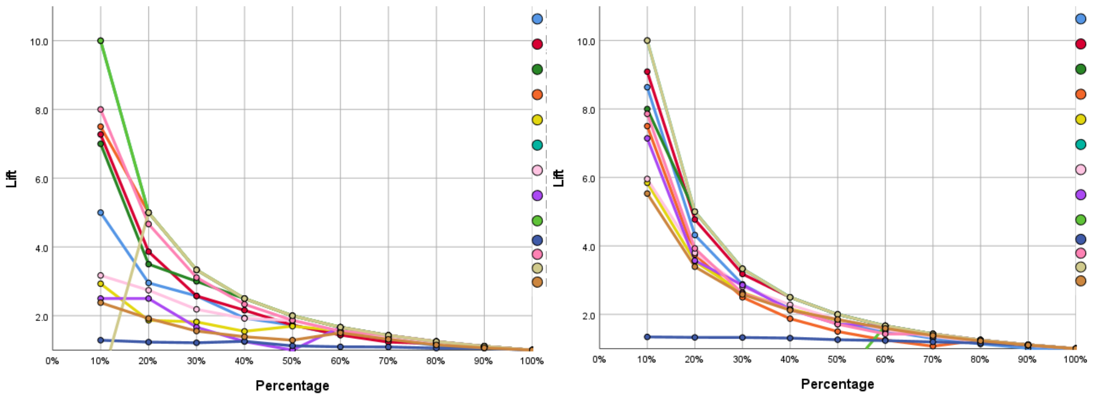


Figure 7.5. Lift chart for models based upon a) Spatial, b) Personal, and c) Infrastructure variables

There are three different predictive models constructed using the following input variable types:

i) Spatial,

ii) Personal, and

iii) Infrastructure variables.

In all these built models with the 'riskiest environmental subset' output, significantly high prediction accuracy is achieved. The models can take 13 output values; hence an ideal 100% accurate model will have an AUROC value of 13. The following AUROC values are obtained for each model:

i) Spatial: 12.36 (95%),

ii) Personal: 10.22 (79%), and

iii) Infrastructure variables: 11.11 (85%),

Average accuracy of 11.23 (86%) is achieved in these three models. The accuracy achieved for the least accurate model (i.e. personal attribute) is significantly higher compared to available models in the literature (e.g. (Peltola and Kulmala, 2010) found an error of more than 2/3 in the Finnish TRAVA safety model for a cyclist, (Yannis *et al.*, 2015) found that due to inaccuracy, around 70% of the European countries either do not or rarely use crash prediction models). Although the present models in the literature primarily serve their intended purpose, the cyclist model's must consider the specific safety variable such as the variable environmental conditions, as demonstrated in this section.

The individual prediction capability of each of the 13 output subgroups that each model can take is evaluated separately. The following median prediction accuracy is achieved for each model:

i) Spatial: 98%,

ii) Personal: 87%, and

iii) Environmental model: 79%.

This establishes the credibility of the constructed model, as both the overall model accuracy and individual output variables prediction is consequentially high. This can be attributed to the ability of deep learning methodology to model complex non-linear relationships. The crashes are multifactored, and the relationship between contributory factors is highly non-linear and complex. Hence, it can be inferred that deep learning is a valuable methodology for road safety investigation to develop accurate and efficient nanoscopic safety models.

7.4. Causal Inference model

After developing predictive models, it is essential to estimate the importance of each input variable. The deep neural network is used to estimate the importance of each input variable in the first step. The Chi-square test is then used for statistical validation, and the association is estimated using Cramer V and Cohem table.

7.4.1. Importance of input variables

The data learning model's critical variables are identified through the variable, and normalised significance (Table 7.5), based upon both testing and validation data sets.

Table 7.5. Normalised importance of input variables in the three constructed models

Variable		I	N_I
Spatial	Hour	0.281	100.0
	Number of Vehicles	0.168	59.7
	Month	0.264	93.7
	Day	0.179	63.8
	Weekday or Weekend	0.108	38.2
Personal	Driver Gender	0.166	48.2
	Driver Age Group	0.281	81.5
	Age and Gender	0.345	100.0
	Journey Purpose of Driver/Rider	0.208	60.3
Infrastructure	Road Type	0.083	82.8
	Speed Limit	0.085	84.8
	1st Road Class	0.073	73.0
	Road hierarchy level	0.076	76.0
	Road hierarchy level and direction	0.092	91.2
	Junction Detail	0.086	85.6
	Junction Control	0.070	69.4
	2nd Road Class	0.089	88.9
	Vehicle Manoeuvre	0.101	100.0
	Carriageway Hazards	0.078	77.1
	Road Location of Vehicle	0.084	83.3

	Junction Location of Vehicle	0.082	81.3

where I = Importance and N_I = Normalised importance in percentage

In the spatial model, the most critical variables are the hour and month in which the journey is undertaken. The hour and month are also correlated with lighting conditions; however, the majority (>80%) of crashes have occurred in daylight. Both these variables are a representation of the traffic flow regime. The number of vehicles that are involved in the crash is not a significant variable, as the overall traffic flow regime that the cyclist is exposed to during the entire trip is a critical variable (see (Parkin, Wardman and Page, 2007; Stewart and McHale, 2014; TfL, 2016)). Safety is negatively affected as the number of variables considered by the cyclist increases (safety law of cognitive capability (Elvik, 2006)). This increase in the variable during the entire trip imparts the unsafeness in the interaction. This leads to conclude that the traffic flow regime directly impacts the cyclist probable riskiest environmental condition. More in-depth insight and conceptualisation of these variables are required to understand and quantify the impact of different traffic flow regimes on cyclists under different environmental conditions. Such work will also have future implications. This can lead to the development of a real-time autonomous route selection model based upon the prevalent flow regime and environmental conditions.

In the personal variable model, the most critical variable is the age and gender combined (100%), followed by driver age (81%), journey purpose (60%), and gender of the trip maker (48%). The rider age and gender impact how a rider reacts to varying environmental conditions (vulnerability and experience of different age groups). The rider belonging to different ages and gender have varied physical and cognitive abilities, thereby reacting differently to varied adverse environmental conditions. The result contributes to the understanding of how the rider personal attributes affect their safety. Although age is an expected variable, results have shown that both gender and age combine to affect the safe usage of infrastructure under varied environmental conditions. However, gender alone is the least significant variable. An in-depth understanding and quantification of personal attributes on cyclist safety are presented in Chapters 5 and 6.

In the infrastructure model, the most critical variable is the vehicle manoeuvre (100%), followed by road hierarchy level and direction (91%), second road class (89%), junction detail (86%), and speed limit (85%). The least essential variable is the control employed at the junction. This lead to infer that the environmental conditions become critical when the cyclist must perform specific manoeuvres while interacting in the natural road environment. This is followed by the difference in road hierarchy level and corresponding direction of change in the hierarchy of road networks in which the cyclist is required to perform these specific manoeuvres. The third variable is the second road class. The road hierarchy level and direction and the second road class are correlated with each other. The variable of road hierarchy level and direction signify the difference between the first and second functional road classes. The following important variable is junction details and speed limit. Therefore, it can be concluded that, at intersections, environmental conditions become critical based upon the specific riding manoeuvres, the difference in road hierarchy level and direction of the change in road hierarchy, and junction details. These are the most critical infrastructure parameters, affecting safe usage of the infrastructure under varying environmental conditions.

The novel variable introduced in this research, i.e., road hierarchy level and direction, is a critical safety variable. This can be attributed to a sudden change in driver behaviour, infrastructure parameters, and change in traffic flow regimes (which has been found critical in the spatial model). Such scenarios do not affect the motorists, as they are required by law to change the speed (with the change in the road hierarchy) and adhere to the speed limit on specific roads. The cyclist needs to make an immediate change in its riding style, the relative safety margin of errors, and its manner of interaction with the motorists. The motorist may start sudden accelerations, as they may want to accelerate quickly, if they have moved to a higher hierarchical functional road class, negatively affecting its interaction with the cyclists. The roadway design elements also change drastically due to a change in the road hierarchy (see (DMRB TD9/93, 1993; Highways England, 2016)). The cyclist is more susceptible to these changes, whereas these infrastructure elements are designed specifically for the motorists and their expected manoeuvres. The research reinforces the need of planning and designing the infrastructure to move towards a more holistic approach while considering this vulnerable road user's limitations. Suppose a sustainable urban transport system is to be achieved. In that case, the cycling mode share must increase by many folds. The work on scenario analysis to achieve sustainability in transportation in Tyne and Wear county (study area) highlighted the importance of increasing the cyclist modal share (Bell CBE *et al.*, 2016). This increase can only be achieved if we make cyclists the pivot of infrastructure design and network planning.

7.4.2. Statistical validation

The association between the target variable of the deep learning neural model (riskiest environmental conditions) and its input variables is tested statistically using the Chi-square test (Table 7.6). Their strength of association with the riskiest environmental conditions is determined through the Cramer V value and Cohen table.

Table 7. 6. Chi-square test for testing association between input variables and environmental conditions

Variable	χ^2	D_f	p-value	H	V	A_T
Hour	2488.8	13	0.01	H_1	0.24	M
Number of Vehicles	130.1	4	0.01	H_1	0.1	S
Month	1080.9	11	0.01	H_1	0.18	M
Day	163.2	6	0.01	H_1	0.09	M
Weekday or Weekend	14.6	1	0.33	H_0	n/a	n/o
Driver Gender	24.1	1	0.03	H_1	0.09	
Driver Age Group	267.0	6	0.01	H_1	0.11	M
Age and Gender	402.3	13	0.001	H_1	0.10	S
Journey Purpose of Driver/Rider	233.9	5	0.01	H_1	0.12	S
Road Type	80.3	5	0.01	H_1	0.07	S
Speed Limit	348.2	5	0.01	H_1	0.15	M
1st Road Class	167.6	4	0.01	H_1	0.11	S
Road hierarchy level	163.4	4	0.01	H_1	0.11	S
Road hierarchy level and direction	225.4	8	0.01	H_1	0.09	S
Junction Detail	342.4	8	0.01	H_1	0.12	S
Junction Control	164.3	3	0.01	H_1	0.13	S

2nd Road Class	241.6	5	0.01	H_1	0.12	S
Vehicle Manoeuvre	311.1	13	0.01	H_1	0.09	S
Carriageway Hazards	144.5	4	0.01	H_1	0.11	S
Road Location of Vehicle	127.1	7	0.07	H_0	n/a	n/o
Junction Location of Vehicle	206.8	8	0.01	H_1	0.09	S

where D_f = degree of freedom, H = hypothesis adopted, H_o; Null hypothesis: Interaction in the risky environment is independent of the variable, H_1; Alternate Hypothesis: Interaction in the risky environment is dependent on the variable, V = Cramer V value, χ^2 = Pearson chi-square value, A_T = Type of the association, S = Small, M = Medium, and *n/o* = no association

These results have depicted that the critical variables identified through deep learning neural networks are associated with the risky environment at a 95% confidence interval. This is further validated by the Cramer V value and the corresponding interpretation using the Cohem table. The two variables, i.e., weekday or weekend, and vehicle road location, are not statistically associated with the riskiest environmental conditions; the same result from deep learning variable importance. The variables identified with a medium level of association (hour, month, day, age, speed limit) have been identified by deep neural networks as critical, having normalised importance greater than 80%. Thereby validating deep learning results statistically and developing requisite confidence for model application and policy implications.

7.5. Multiple logistic regression model

There are two environmental variables of variable lighting and meteorology; hence, two regression models are developed.

7.5.1. Lighting conditions

In the first logistic regression model, the lighting conditions are used as the response variable. The results for the final statistically significant variable model are presented in Table 7.7.

Table 7.7. Multiple logistic regression model with lighting conditions as the response variable

	Coefficient	*p*-value	*OR*	95% C.I for OR	
				L_L	U_L
Hourly flow rate (x_1)	-0.94	0.00	0.39	0.36	0.43
Traffic flow regime (x_2)	0.50	0.01	1.65	1.22	2.23
Peak (x_3)	1.15	0.01	3.16	1.72	5.79
Driver gender (x_4)	-0.63	0.02	0.54	0.36	0.80
Weather (x_5)	0.77	0.00	2.17	1.54	3.06
Constant	-2.45	0.00	11.44		

where *OR* = Odds ratio and *C.I* = confidence interval, L_L = Lower limit, and U_L = Upper limit.

The following variables have a statistically significant relation at a 95% confidence interval with the subsequent odds ratio of:

i) Hourly flow rate: 0.39,

ii) Traffic flow regime: 1.65,

iii) Whether the journey is being made in peak hour: 3.16,

iv) Driver gender: 0.54, and

v) Weather: 2.17.

The modelling results in the final statistical equation, presented in Eq 7.1.

$$Logit(p) = \ln \frac{p}{1-p} = -a_o - a_1 x_1 + a_2 x_2 - a_3 x_3 + a_4 x_4 + a_5 x_5 \qquad (7.1)$$

where x_1 = Hourly flow rate, x_2 = Traffic flow regime, x_3 = Peak, x_4 = Driver gender, and x_5 = Weather.

The estimated coefficient $a_o, a_1, a_2, a_3, a_4, a_5,$ and a_6 values are 2.45, 0.94, 0.5, 1.15, 0.63, 0.77, respectively.

$$p = \frac{e^{logit(p)}}{1 + e^{logit(p)}} \qquad (7.2)$$

where $p = \text{probability of darkness crashes}$, and $1 - p = \text{probability of daylight crashes}$

From the logistic regression model, we can interpret that a unit increase in the hourly traffic flow increases the probability of daylight crashes by 2.55 times. Whether the journey is being performed at peak or not has a significant impact on the particular lighting condition's riskiness. The probability of darkness crashes increases by 3.2 times if the journey is being made in the peak compared with non-peak. The only conditions in which the peakiness of traffic flow conditions is reached during adverse lighting conditions are the winter months. Hence, we can conclude that the combination of adverse lighting conditions and a high traffic flow can significantly affect an infrastructure type's riskiness. The flow regime's relation is investigated by modelling the flow regime variable with the lighting conditions to validate this hypothesis further. A statistically significant relationship between the two variables, with an increase in the flow regime, results in an increase in the probability of darkness crashes by 1.7 times. The traffic flow regime is modelled as 0 = overnight flow, 1 = day flow, 2 = morning peak flow, 3 = evening peak flow. Therefore, these adverse lighting conditions, especially during the winter month, having a high traffic flow and improper lighting conditions, are critical safety variables for a cyclist. This type of adverse condition negatively affects the safety of cyclists.

The gender is modelled as 0 for male, and 1 for females. A negative relationship is obtained between gender and lighting conditions. The initial results show that males are more susceptible to bad light by a factor of 1.87(1/0.54). This can be attributed to less risk-taking behaviour by female cyclists. The other factor that needs to be considered is that lighting conditions are also a mode choice variable for female riders (Heinen, Maat and van Wee, 2011). The females are reported to dislike the cycling mode during darkness.

The other environmental condition variables, i.e., the weather conditions (modelled 0 for fine and 1 for wet), has a statistically significant relationship with the lighting conditions. The probability of a dark crash increases by 2.2 times as the meteorological conditions change from satisfactory to wet. Therefore, it can be concluded that these two environmental variables are significant, interlinked to each other, and act in combination to affect infrastructure safety for a rider.

7.5.2. Meteorological condition

In the second logistic regression model, meteorological conditions are the response variable; modelled 0 for fine weather and 1 for wet conditions. The statistically significant variable model results are presented in Table 7.8, with the following variables having a statically significant relationship at a 95% confidence interval along with the latter odds ratio:

i) Collision severity: 0.56,

i) Hourly flow rate: 0.82,

ii) Whether the journey is being made in peak hour: 1.63, and

iii) Lighting conditions: 2.15.

The final statistical equation is presented in Eq 7.2.

Table 7.8. Multiple logistic regression model with meteorological conditions as the response variable

	Coefficient	p-value	*OR*	OR^{-1}	95% *C.I* for *OR*	
					L_L	U_L
Collision severity (x_1)	-0.59	0.00	0.56	1.79	0.39	0.79
Hourly flow rate (x_2)	-0.20	0.00	0.82	1.22	0.75	0.90
Peak (x_3)	0.49	0.01	1.63	0.61	1.11	2.38
Lighting conditions (x_4)	0.76	0.00	2.15	0.47	1.53	3.02
Constant	-0.96	0.00	0.38	2.63	n/a	n/a

where *OR* = Odds ratio and *C.I* = confidence interval, L_L = Lower limit, and U_L = Upper limit.

$$Logit(p) = \ln\frac{p}{1-p} = -a_o - a_1 x_1 - a_2 x_2 + a_3 x_3 + a_4 x_4 \qquad (7.3)$$

where x_1 = Collision severity, x_2 = Hourly flow rate, x_3 = Peak, and x_4 = Lighting conditions.

with $a_{o,} a_1, a_2, a_3,$ and a_4, estimated as 0.96, 0.59, 0.2, 0.49, and 0.76 respectively.

$$p = \frac{e^{logit(p)}}{1 + e^{logit(p)}} \qquad (7.4)$$

where p = probability of darkness crashes, $1 - p$ = probability of daylight

crashes

The crash severity and meteorological conditions have a statistically significant relationship. As the metrological condition changes from fine to wet, the probability of a severe crash decreases significantly. In an adverse meteorological condition, the probability of slight crashes increases by 1.8 times. This can be due to two primary reasons. Firstly, drivers are more cautious in adverse conditions, so even if a crash/fault happens, it is much more likely to lead to a low-intensity crash. The other postulated reason is that the crash frequency increases significantly; however, such an increase will be uniform across severity. Even if there is only an increase in slight crashes and overall safety has decreased, some mitigation of present crashes from slight to severe should have occurred. This leads to conclude that drivers and cyclist riders are extra careful during adverse environmental conditions, reinforcing the traditional crash theory that the human element is a critical variable affecting crashes. Consequently, the present need is to invest more in human training to change the road user attitude; such a shift is critical for increasing road safety. As the transportation system moves towards autonomous vehicular infrastructure and vehicles, it is essential to achieve the same along with automation. Besides, during the uptake of the autonomous transportation system, there will be a mixed environment in which the autonomous infrastructure and non-autonomous vehicles and infrastructure are operating together. We are presently at the doorway towards the fourth industrial revolution of transportation automation; therefore, such human behaviour needs to be considered, modelled, and included in the infrastructure's planning and operational strategy. It is essential to shift the focus from developing a transportation network based upon how humans should use it to how they actually use it. These results also validate the results of section 7.5.1. Men face a higher risk in wet conditions. The underlying reason being the human element. The female riders are relatively more careful than males during adverse meteorological and lighting conditions. It is already a well-established fact that women live longer than men.

There is a negative relationship between the hourly flow rate and adverse meteorological conditions. The phenomena of Safety in Numbers (SiN) is an established phenomenon in which there is a relative increase in cyclist safety during higher flow. Even when the user faces adverse conditions, these conditions' effect is lower than the increase in safety due to SiN. The traffic flow is also higher during the day hours. However, whether the journey is being made is the peak or not is having a positive relationship. During the peak hours, there is a higher pressure on the motorists, as their journey times may have increased significantly due to congestion and a corresponding higher number of conflicts. Inevitably, as the number of variables that the cyclists have to adhere to increases, the safety decreases (safety law of complexity (Elvik, 2006)). Therefore, based upon the results, we can conclude that as the vehicular flow increases, the probability of risk per vehicular interaction decreases due to the SiN phenomenon; however, as the conflicts increase due to congestion (peak), there is a decrease in the overall net safety.

As the lighting conditions change from daylight to dark, the probability of crashes in wet climate increases by 2.2 times compared with the dry weather crashes, reinforcing the combined adverse effect of these variables to affect the safety of an infrastructure for a rider.

7.6. Chapter Summary

In this chapter, we have investigated the effect of varying environmental conditions on cycling safety. Combining multiple frameworks demonstrates that a road safety model can be constructed with significantly high accuracy (spatial 95%, personal 79%, and infrastructure 85%, an average of 86% across all models) and predictive power.

It is shown that the safe usage of infrastructure depends on the environmental conditions that a rider is subjected. The adverse conditions pose varying challenges for the rider while using the infrastructure, which results in both physical and cognitive strains. The probability of darkness crashes increases by 3.2 times if the journey is made in the peak compared with non-peak. It is found that the combination of adverse lighting conditions and a high traffic flow can significantly affect an infrastructure type's riskiness. The males are more susceptible to bad light, attributed to less risk-taking behaviour by female cyclists. The crash severity and meteorological conditions have a statistically significant relationship. As the metrological condition changes from fine to wet, the probability of a severe crash decreases significantly. There is a negative relationship between the hourly flow rate and adverse meteorological conditions. It is found that, even when the user faces adverse conditions, the effect of these conditions is lower compared with the increase in safety due to the safety in numbers (SiN) phenomenon. The probability of a dark crashes increases as the meteorological conditions change from being satisfactory to wet. Similarly, as the lighting conditions change from daylight to dark, the wet crashes' probability increases. Therefore, the varied environmental conditions need to be modelled effectively and efficiently to develop the requisite knowledge-driven cycling infrastructure approach.

Chapter 8.

Development of a predictive model and identification of governing variables for micro-infrastructural parameters

8.1. Introduction

In Chapters 5, 6, and 7, the critical variable of age, gender, and varied environmental conditions are modelled. The subsequent phase is to model the micro-infrastructure parameters. This chapter aims to predict the riskiest micro-infrastructure parameters of: a) road type, b) junction details, c) vehicle manoeuvre and d) junction location. This is achieved through an intelligent methodological paradigm consisting of deep learning neural network, variable importance, principal component analysis, and ordinal regression (Fig 8.1).

The primary motivation for the study is that there are very few works that have attempted to undertake such modelling. Presently, such a model is absent to predict the micro infrastructure parameters/ characteristics for a cyclist infrastructure. This limitation has negatively affected the planning and design of cycling networks. This limitation must be addressed to improve infrastructure design and planning. Through such modelling, requisite confidence for policy implications and knowledge-driven recommendation measures can be achieved. This study will improve the understanding of how different input parameters of different traffic flow regimes, environmental conditions, rider personal attributes, and micro infrastructure parameters affect the safe usage of infrastructure for a particular rider. The primary objectives of this chapter are, to:

1. Develop an understanding of the riskiness of the cyclist's interaction with the infrastructure.
2. Test the hypothesis that it is possible to predict the riskiest infrastructure based on cyclist's attributes under specific environmental and traffic flow conditions
3. Develop an intelligent safety modelling framework and predictive models for the riskiest a) Road type, b) Junction details, c) Vehicle Manoeuvre, and d) Location with the junction.
4. Develop an understanding of how different variables act alone and make a particular infrastructure riskiest in combination with each other.

In the next section, predictive models are explained, followed by governing variable model in Section 8.3, exploratory data analysis in Section 8.4, and ordinal regression in Section 8.5. Finally, the chapter summary is presented in Section 8.6.

8.2. Deep Learning predictive models

There are four accurate predictive infrastructure models constructed. Their principal characteristics are described in Table 8.1, the structure is illustrated in Fig 8.1, and characteristics are described through ROC curves (Fig 8.2). For all the four models, each output value's ROC curves are towards the top left-hand corner, depicting a significantly high accuracy, especially in model 2 (junction detail and control) and model 4 (junction location of the vehicle). For numerically quantifying distinguishable

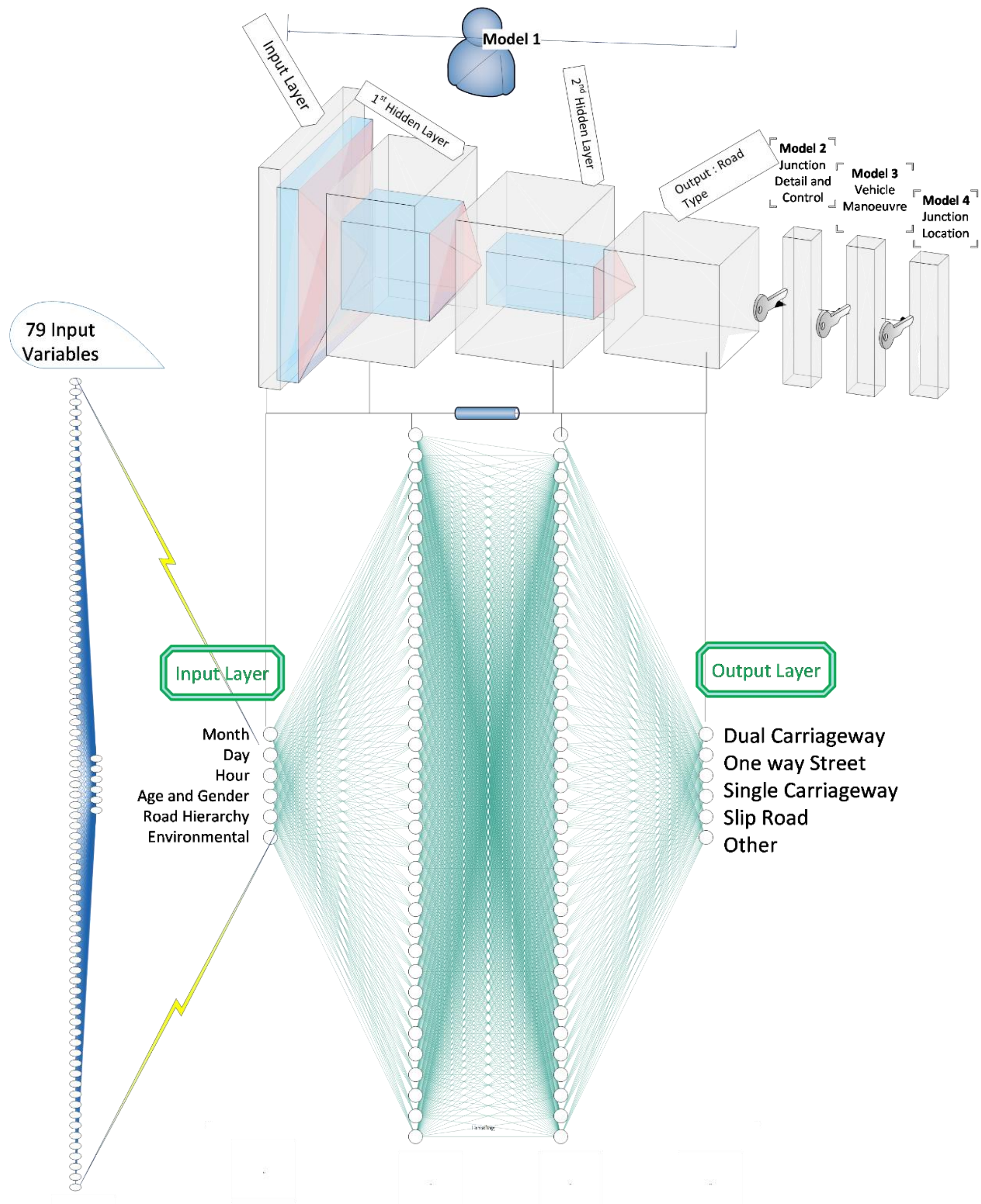
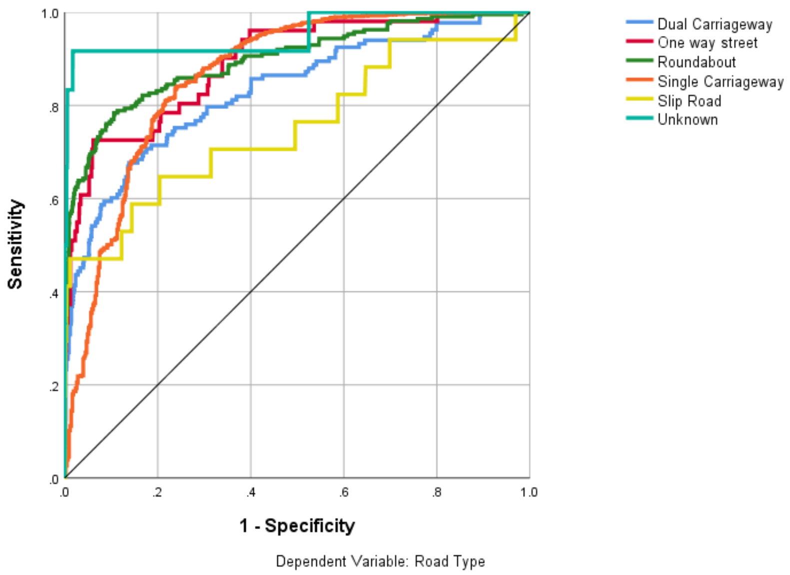
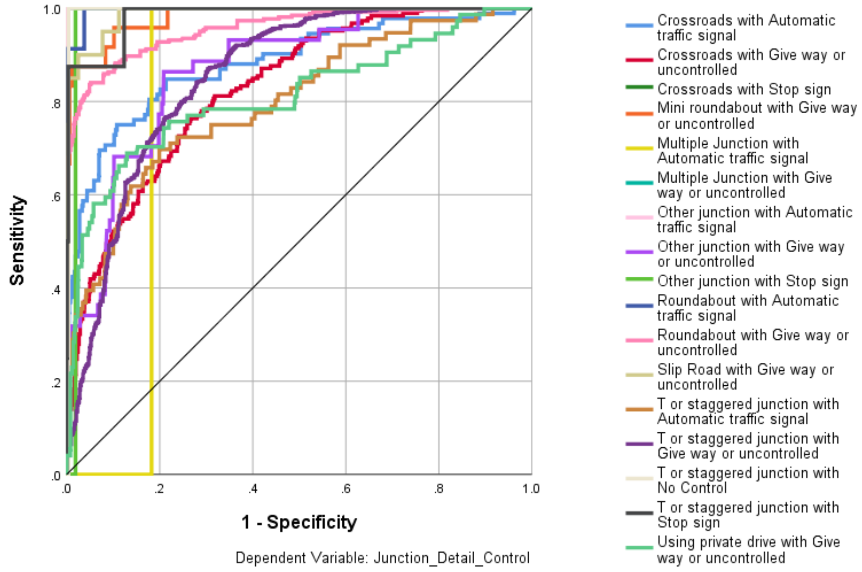


Figure 8.1. Deep learning neural network structure

power of the models, between riskiest and non-risky infrastructure type, AUROC values are presented in Table 8.2. Significantly high accuracy is achieved in all the models across the spectrum with average (median) accuracy of 86% (88%) for model 1, 93% (98%) model 2, 88% (90%) model 3, and 95% (94%) model 4 respectively. Thereby, validates the hypothesis that it is possible to predict the riskiest infrastructure based on a particular cyclist's specific input variable under the specific environmental and traffic flow conditions. It is well established in the literature that the present safety models cannot be used to model cyclist infrastructure due to their inability to model their safety accurately. An evaluation of the major traffic modelling simulation software, including PTV VISSIM, AIMSUM, TEXAS, and PARAMICS, demonstrated an inability to effectively and effectively simulate cyclists (Gettman *et al.*, 2008). An average accuracy of around 90% is achieved in the constructed safety models, higher than presently available in the literature. To validate the use of a complex computational methodology, such as deep learning compared with the simple probability-based model, lift charts are also developed (Fig 8.3). The lift achieved in model 1 (5-9 times), model 2 (4-10 times), model 3 (4-10 times), and model 4 (2.5-10) is significantly high, e.g. model 1 can better undertake prediction five to nine times higher than the probability-based model. However, there are few outliers, which is due to the minority class of the output variables. The models contribute towards knowledge, which can be used to predict the safe infrastructures better, that the practitioners and researchers can use.

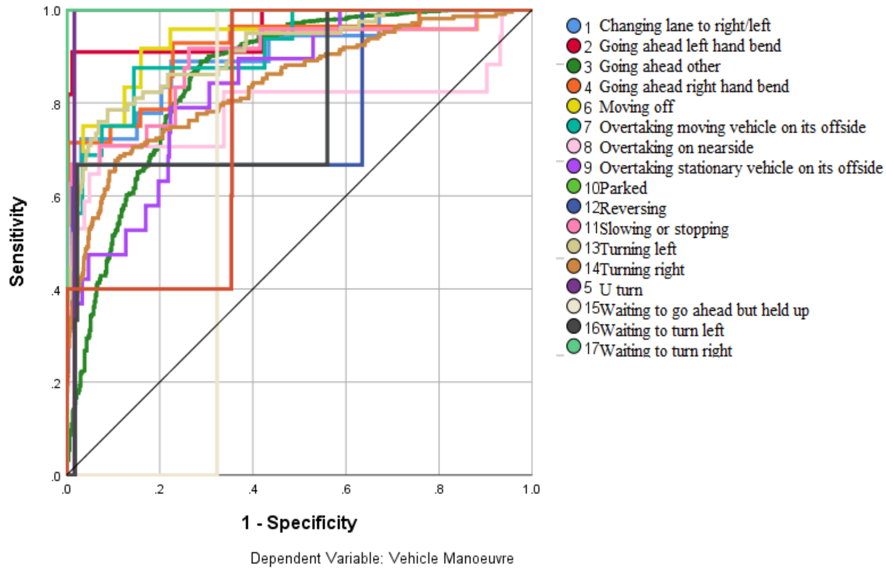


a)



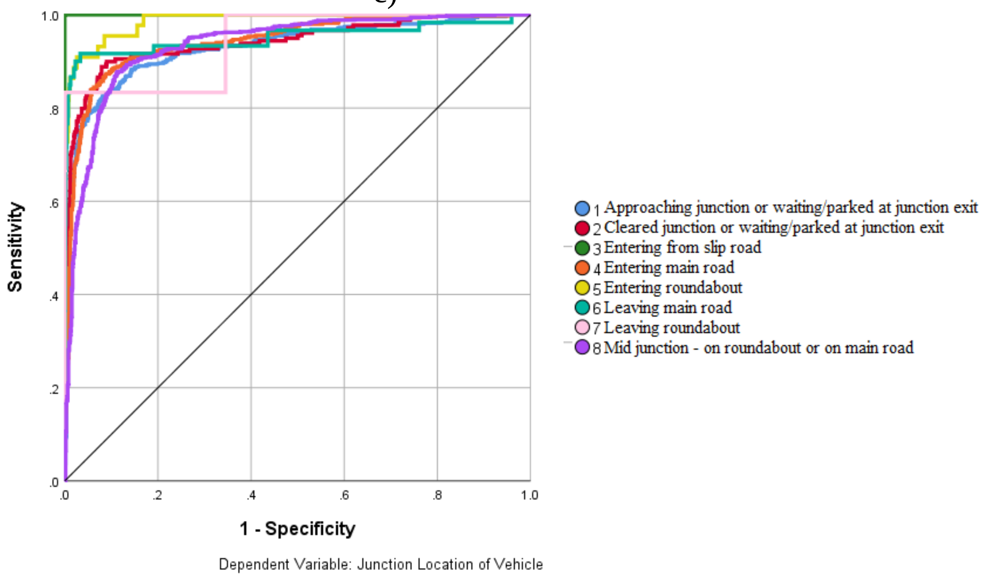
1.0
.8
.6
.4
.2
.0
Sensitivity
.0
.2
.4
.6
.8
1.0
1 - Specificity
Dependent Variable: Junction_Detail_Control
Crossroads with Automatic traffic signal
Crossroads with Give way or uncontrolled
Crossroads with Stop sign
Mini roundabout with Give way or uncontrolled
Multiple Junction with Automatic traffic signal
Multiple Junction with Give way or uncontrolled
Other junction with Automatic traffic signal
Other junction with Give way or uncontrolled
Other junction with Stop sign
Roundabout with Automatic traffic signal
Roundabout with Give way or uncontrolled
Slip Road with Give way or uncontrolled
T or staggered junction with Automatic traffic signal
T or staggered junction with Give way or uncontrolled
T or staggered junction with No Control
T or staggered junction with Stop sign
Using private drive with Give way or uncontrolled

b)



1.0
.8
.6
.4
.2
.0
Sensitivity
.0
.2
.4
.6
.8
1.0
1 - Specificity
Dependent Variable: Vehicle Manoeuvre
1 Changing lane to right/left
2 Going ahead left hand bend
3 Going ahead other
4 Going ahead right hand bend
6 Moving off
7 Overtaking moving vehicle on its offside
8 Overtaking on nearside
9 Overtaking stationary vehicle on its offside
10Parked
12Reversing
11Slowing or stopping
13Turning left
14Turning right
5 U turn
15Waiting to go ahead but held up
16Waiting to turn left
17Waiting to turn right

c)



1.0
.8
.6
.4
.2
.0
Sensitivity
.0
.2
.4
.6
.8
1.0
1 - Specificity
Dependent Variable: Junction Location of Vehicle
1 Approaching junction or waiting/parked at junction exit
2 Cleared junction or waiting/parked at junction exit
3 Entering from slip road
4 Entering main road
5 Entering roundabout
6 Leaving main road
7 Leaving roundabout
8 Mid junction - on roundabout or on main road

d)

Figure 8.2. ROC curves of a) model 1: road type, b) model 2: junction detail and control, c) model 3: vehicle manoeuvre and d) model 4: junction location of vehicle

Table 8.1. Network structure of the four predictive infrastructure models

Network Information					
Model No.		1	2	3	4
Input Layer	Number of Units	79	83	100	109
Hidden Layer(s)	Number of Hidden Layers	2	2	2	2
	Number of Units in Hidden Layer 1	35	35	35	35
	Number of Units in Hidden Layer 2	35	35	35	35
	Activation Function: Hyperbolic tangent				
Output Layer	Dependent Variables	Road Type	Junction Detail and Control	Vehicle Manoeuvre	Junction Location of Vehicle
	Number of Units	6	17	18	8
	Activation Function : SoftMax				
Error Function	Cross Entropy Error	637.6	661.1	528.5	764.0

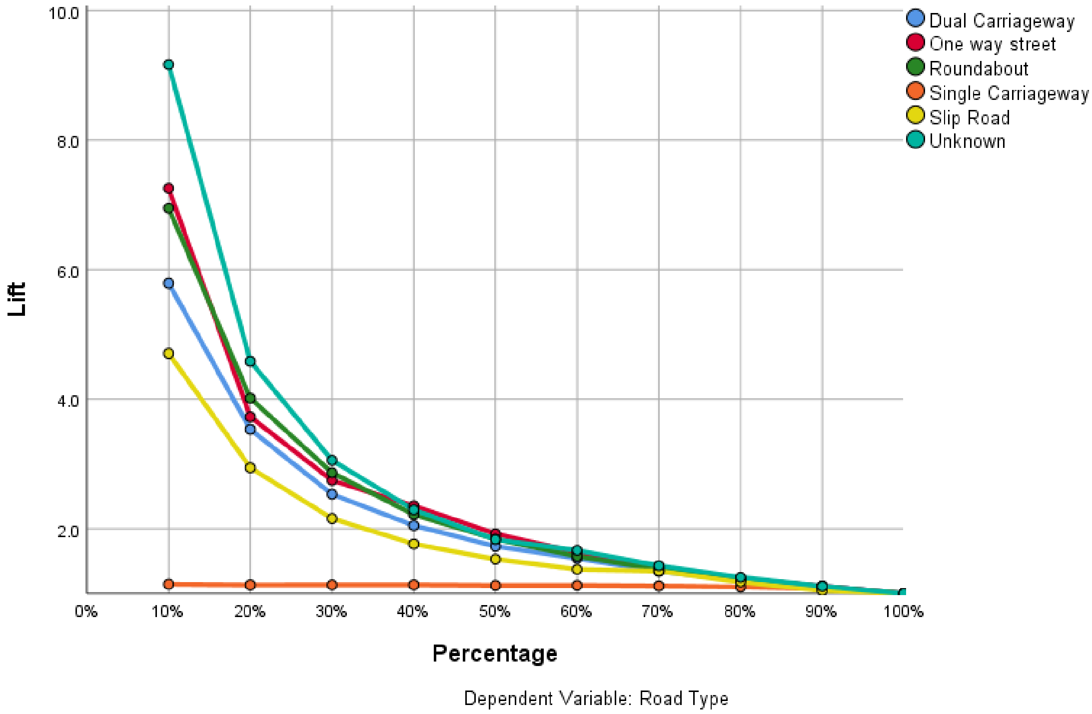
Table 8.2. AUROC values of the constructed models

Model 1		Model 2		Model 3		Model 3	
Road Type	A_R	Junction Detail Control	A_R	Vehicle Manoeuvre	A_R	Junction Location of Vehicle	A_R

Dual Carriage way	0.83	Crossroads with Automatic traffic signal	0.88	Changing lane to right/left	0.902	Approaching junction or waiting/parked at junction exit	0.93
One way street	0.89	Crossroads with Give way or uncontrolled	0.83	Going ahead left hand bend	0.96	Cleared junction or waiting/parked at junction exit	0.94
Roundabout	0.9	Crossroads with Stop sign	0.99	Going ahead other	0.86	Entering from slip road	0.99
Single Carriage way	0.86	Mini roundabout with Give way or uncontrolled		Going ahead right hand bend	0.92	Entering main road	0.94
Slip Road	0.75	Multiple Junction with Automatic traffic signal	0.82	Moving off	0.93	Entering roundabout	0.97
Other	0.95	Multiple Junction with Give way or uncontrolled	0.99	Overtaking moving vehicle on its offside	0.91	Leaving main road	0.95
		Other junction with Automatic traffic signal	0.99	Overtaking on nearside	0.79	Leaving roundabout	0.94
		Other junction with Give way or uncontrolled	0.87	Overtaking stationary vehicle on its offside	0.84	Mid junction - on roundabout or on main road	0.94
		Other junction with Stop sign	0.98	Parked	0.99		

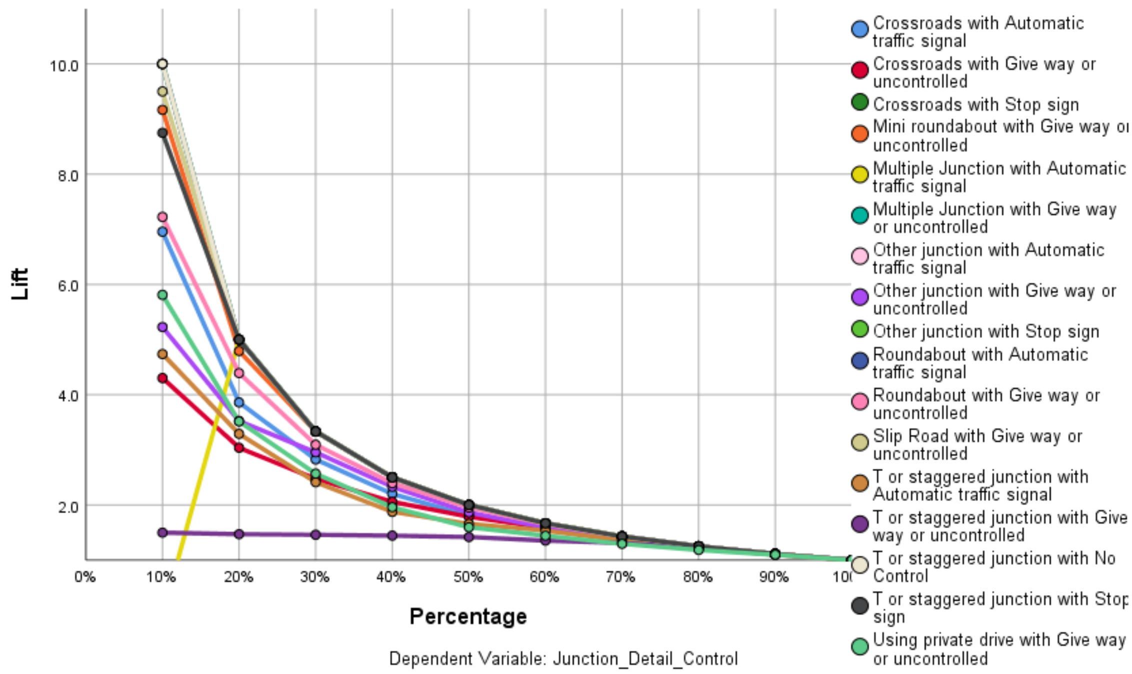
		Roundabout with Automatic traffic signal	0.99	Reversing	0.78		
		Roundabout with Give way or uncontrolled	0.96	Slowing or stopping	0.89		
		Slip Road with Give way or uncontrolled	0.98	Turning left	0.91		
		T or staggered junction with Automatic traffic signal	0.8	Turning right	0.84		
		T or staggered junction with Give way or uncontrolled	0.85	U turn	0.98		
		T or staggered junction with No Control	0.99	Waiting to go ahead but held up	0.8		
		T or staggered junction with Stop sign	0.98	Waiting to turn left	0.99		
		Using private drive with Give way or uncontrolled	0.81	Waiting to turn right	0.79		
Mean	0.86	Mean	0.93	Mean	0.88	Mean	0.95
Median	0.88	Median	0.98	Median	0.9	Median	0.94

where A_R = *Area*



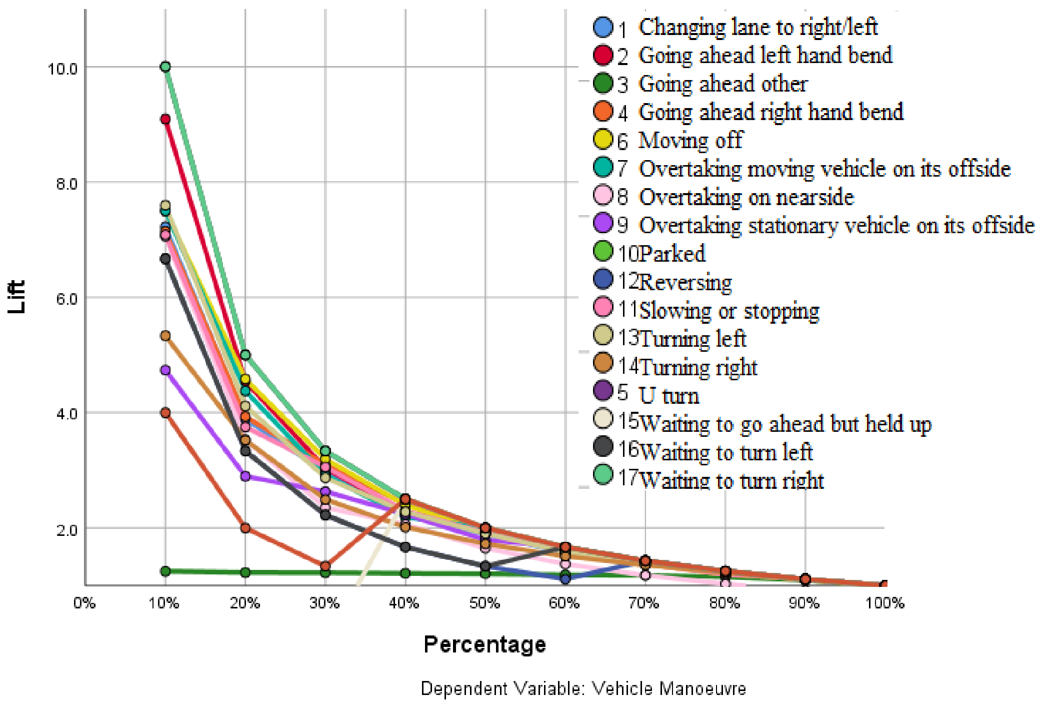
Lift
Percentage
Dependent Variable: Road Type
Dual Carriageway
One way street
Roundabout
Single Carriageway
Slip Road
Unknown

a)

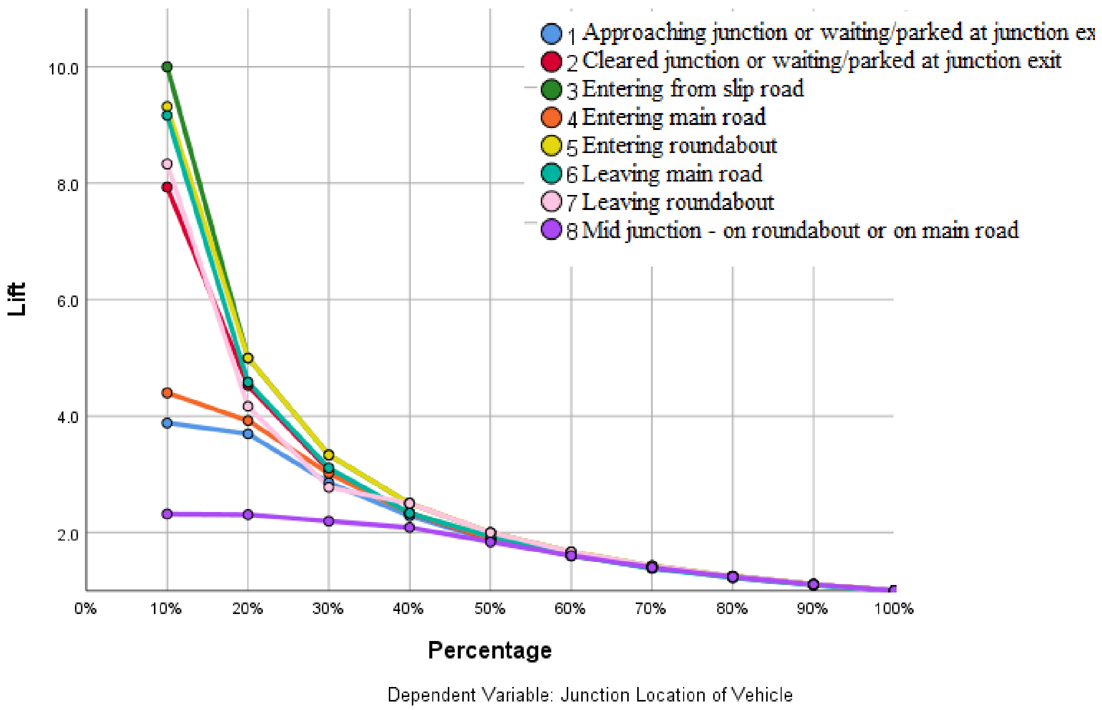


Lift
Percentage
Dependent Variable: Junction_Detail_Control
Crossroads with Automatic traffic signal
Crossroads with Give way or uncontrolled
Crossroads with Stop sign
Multiple Junction with Automatic traffic signal
Multiple Junction with Give way or uncontrolled
Other junction with Automatic traffic signal
Other junction with Give way or uncontrolled
Other junction with Stop sign
Roundabout with Automatic traffic signal
Roundabout with Give way or uncontrolled
Slip Road with Give way or uncontrolled
T or staggered junction with Automatic traffic signal
T or staggered junction with Give way or uncontrolled
T or staggered junction with No Control
Using private drive with Give way or uncontrolled

b)



c)



d)

Figure 8.3. Lift Charts of a) model 1: road type, b) model 2: junction detail and control, c) model 3: vehicle manoeuvre and d) model 4: junction location of vehicle

8.3. Governing variable analysis

The critical variable identification from the input of the deep learning model is presented in Tables 8.3 and 8.4. The critical variables affecting the riskiest road type are the environmental conditions, the hour of journey and the difference in the functional road hierarchy level. The environmental conditions have a varied effect on safety; however, their impact on safety varies depending upon the infrastructure parameters. The adverse environment complicates the interactions that a cyclist performs, compounded by the different road infrastructure types. Similarly, the hour of the journey, a representation of the traffic flow regime during the journey's entire trip, and a sudden change in the road hierarchy affect the safe interaction and have a varied effect on safety. As the number of variables that the cyclist must adhere to increases, the interactions get complicated, negatively affecting different infrastructure types. However, the motorist benefits from a closed and secure machine at their disposal, contrary to the cyclist. The micro infrastructure parameters are designed as per the motorist requirements (see (DMRB TD9/93, 1993; DMRB TD 42/95, 1995)). Therefore, infrastructure poses a unique risk to the cyclist, which gets compounded as the interaction with infrastructure and motorists is perplexed. There is a need for the planning and design to move toward a cyclist centric approach rather than the present motorists focussed. For the riskiest junction details, the most critical variable is the road type, an expected variable as the type of junction and the road type are highly correlated. The following most crucial variable is the hour and month of the journey, representing the traffic flow regime plying.

The riskiest vehicle manoeuvre is significantly affected by age and gender, followed by junction detail and control, road hierarchy level, and hour of journey. The specific vehicle manoeuvres require individual physical and cognitive capabilities, which riders belonging to different ages and gender possess, and therefore this is an expected most critical variable. Similarly, the specific junction details and control may require the riders to perform particular manoeuvres, affecting the unsafeness, which needs to be incorporated in the modelling and planning of infrastructure. Also, the journey's hour is found to be a significant variable affecting safety. The specific manoeuvres that the cyclist is required to perform can get complicated due to the different traffic flow regimes. The traffic flow regime is an additional variable, which affects safety. Therefore, this combination can be a significant hazard as the number of variables that the road user has to adhere to increases, so does the risk faced (law of complexity (Elvik, 2006)) by the rider.

The riskiest junction location's critical variable is the vehicle manoeuvre, followed by the hour of journey, age and gender of the rider, and road type. Therefore, we can infer that specific locations within the junction are correlated with the riskiest vehicle manoeuvres resulting in a crash. This is again correlated with the age and gender and the journey's hour, like the vehicle manoeuvres variable model. This leads us to conclude that the riskiest vehicle manoeuvres and the riskiest location within the junction riskiest are highly correlated, significantly affected by the rider age and gender and the traffic flow conditions. Therefore, these are dynamic variables, which should be considered while planning the cyclist routes. It is established from the literature that the cyclist does not follow the minimum travel path algorithm (see Dublin city model (Lawson *et al.*, 2013)). The route selected by the cyclist is dependent upon the perceived safety (see (Stewart and McHale, 2014)), which is varied for riders belonging to different ages and gender and the traffic flow regime.

Therefore, the route selection for a particular rider is also varied, varying with the rider attribute and the traffic flow regimes.

The present knowledge in the literature although acknowledges that these variables of traffic flow regime, personal attributes of age and gender, varied environmental conditions and the micro infrastructure variables. However, very few works acknowledge that these variables act in combination with each other to affect the safety of cyclists. The traditional safety theories are based on fatality and accident rates. Numbers alone are insufficient for gaining a complete understanding of road safety and its change over time for a vulnerable road user, such as a rider (Hauer and Hakkert, 1998; Meade and Stewart, 2015). The performance of such prediction models gives long-term projections with the primary purpose of modelling the annual crash, seasonal variance, and detecting key black spots. These are premised on the theory that instantaneous traffic flow accurately reflects the human error that leads to a crash. The underlying assumption is that if the flow increases, the chances of interaction and a crash increase (Hossain and Muromachi, 2009).

Table 8.3. Variable importance

Importance	Model 1	Model 2	Model 3	Model 4
Month	0.14	0.13	0.11	0.11
Day	0.13	0.11	0.10	0.10
Hour	0.18	0.15	0.14	0.13
Age and Gender	0.16	0.13	0.15	0.13
Road Hierarchy level and direction	0.18	0.11	0.14	0.11
Env. (Light and Road surface condition)	0.20	0.14	0.12	0.12

Road Type	n/a	0.23	0.1	0.12
Junction Detail Control	n/a	n/a	.14	n/a
Vehicle Maneuver	n/a	n/a	n/a	.18

Table 8.4. Normalized variable importance

Normalised Importance (%age)	Model 1	Model 2	Model 3	Model 4
Month	72	55	76	63
Day	65	47	71	58
Hour	91	62	94	75
Age and Gender	82	57	100	71
Road Hierarchy level and direction	90	47	95	60
Env. (Light and Road surface condition)	100	59	84	68
Road Type	n/a	100	68	69
Junction Detail Control	n/a	n/a	99	n/a
Vehicle Maneuver	n/a	n/a	n/a	100

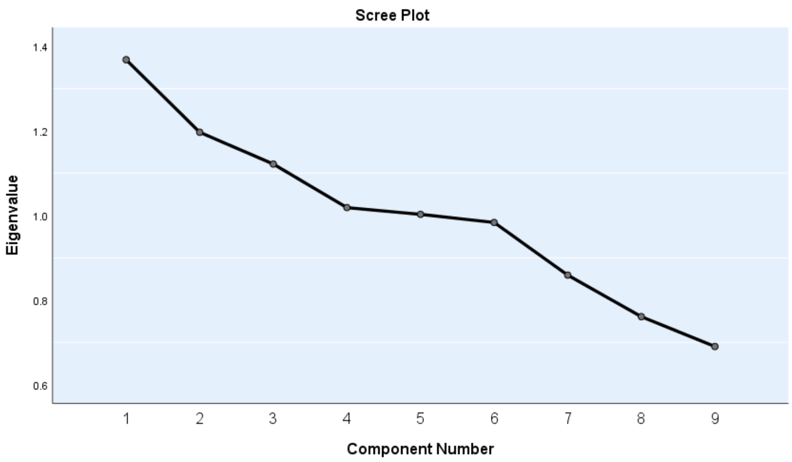
8.4. Exploratory Data Analysis

Principal component analysis with orthogonal rotation (Promax with Kaiser normalisation) is used to determine the combined influence of safety variables. The determinant value is 0.87 >>> 0.00001. As a result, the multicollinearity assumption is met. The Kaiser-Meyer-Olkin verifies the sampling adequacy for analysis, *KMO* value = 0.51, which is acceptable for PCA analysis. There needs to be some correlation between the variables, and if *R* is an identity, then the correlation within the variables will be equal to zero. The assumption is verified using Bartlett's test's, with the null hypothesis that the correlation matrix is an identity matrix; $B = 566$, df = 28, and $p < 0.0001$. Therefore, both the assumptions of the PCA are met.

Table 8.5. Principle component analysis

Principle Component Analysis assumptions		
Determinant		0.83
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.51
Bartlett's Test of Sphericity	Chi-Square	596
	Df	36
	Sig.	0

The initial analysis is performed on eigenvalues for each variable in the data. Five factors have eigenvalues greater than Kaiser criteria of one, and in combination, explain 63 % of the variance. The screen plot (Fig 8.4) shows inflexion that would justify the five factors. The variables from clusters on the same factors suggest that factor 1 represents the mixed variable, factor 2 represents environmental, factor 3 infrastructural, factor 4 represents gender and month, and factor 5 represents the traffic flow conditions. The statistically significant variables at 99.9% confidence interval are determined through the pattern matrix in Table 8.6. for each factor.



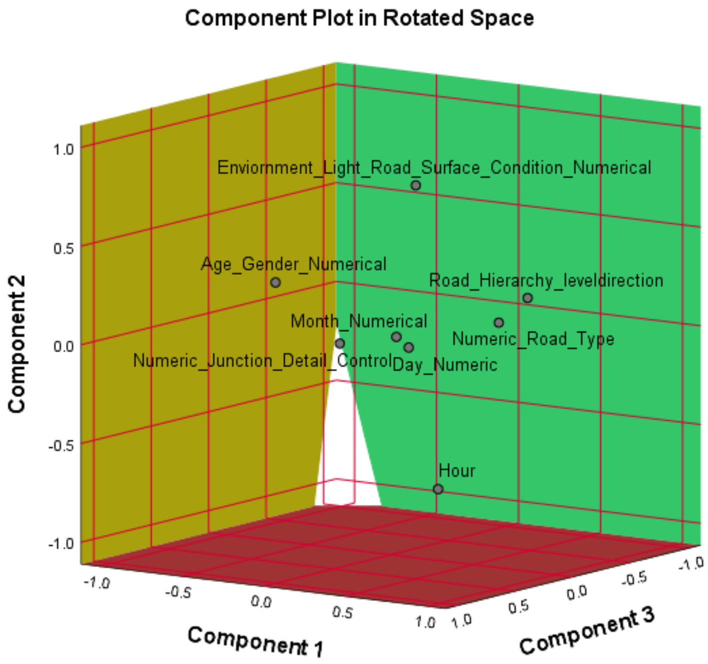


Figure 8.4. Screen plot and the component plot in rotated space in the principal component analysis

Table 8.6. Pattern Matrix

	1 (Mixed)	2 (Env.)	3 (Infra)	4	5 (Day)
Age	-.694				
Road Type	.678				
Environment Condition		.775			
Hour	.311	-.751			
Junction Detail and Control			.803		
Road Hierarchy	.343		-.708		
Gender				.742	
Month				.677	
Day					.953

It is established from the literature that traffic flow conditions during the entire trip can affect safety, rather than just the instantaneous flow regime (see (Elvik, 2006)). Therefore, variables of the hour, month, and day of the journey represent the traffic flow regime during the entire trip of the journey. The statistically significant variables are detected using a pattern matrix; only correlations > 0.3 are used for final evaluation. Factor 1 is characterised by the rider age, riskiest road type and road hierarchy. Thereby suggests that infrastructure variables and rider age act in combination to make a particular situation risky for cyclists. We can deduce that infrastructure variables pose a varying risk to which the riders belonging to different age groups react differently through inverse analysis. The environmental conditions and hour of the journey are associated together in factor 2 (environment). Therefore, the riskiest environmental conditions get compounded by the plying traffic flow regime and act as a significant hazard for the cyclist to deal with. The third component is a combination of the infrastructure variables, inferring that the infrastructure variables alone significantly affect the safety of the cyclists. The fourth component has variables of gender and month. Therefore, the traffic flow regime poses a varying risk to the cyclist to which riders belonging to different genders react differently, affecting their infrastructure's safe usage. The final component is comprised of a single variable, the day of the journey. Hence, this being a single variable in the component explains a higher proportion for the variance, leading us to conclude that traffic flow conditions are alone significant variables affecting the safety of the cyclist.

The study has mathematically validated that the critical safety variables act in combination with each other. Therefore, in the planning and design of transportation networks, situations where a combination of critical factors comprehend need to be accounted for. The study has validated that the Swiss cheese model can be applied for modelling cycling safety. Hence, a future study should focus on developing a heterogeneous Swiss cheese model.

8.5. Ordinal Regression

A regression model is developed (Table 8.7) to predict the output of the riskiest road hierarchy level and direction of change (R_{HL}). This is a novel variable introduced in the study.

Table 8.7. Ordinal regression model to predict R_{HL}

	Variable	*B*	Sig.	Exp (*B*)	95% *C.I* L_B	U_B
Target variable	R_{HL}= -4	-2.15	0.00	n/a	n/a	n/a
	R_{HL}= -3	-1.66	0.01	n/a	n/a	n/a
	R_{HL}= -2	-1.23	0.04	n/a	n/a	n/a
	R_{HL} = -1.	-1.05	0.09	n/a	n/a	n/a
	R_{HL}= 0	1.21	0.05	n/a	n/a	n/a
	R_{HL}= 1	1.42	0.02	n/a	n/a	n/a
	R_{HL}= 2	1.76	0.01	n/a	n/a	n/a
	R_{HL}= 3	2.02	0.00	n/a	n/a	n/a
Independent variable						
Road Type	Dual carriageway	-0.82	0.02	0.44	0.23	0.86
	Slip road	-1.22	0.01	0.30	0.12	0.70
	Other	0				
Junction Detail and Control	Crossroads with Give way or uncontrolled	0.92	0.00	2.50	1.86	3.36
	Multiple Junction with Give way or uncontrolled	2.04	0.00	7.71	2.12	28.05
	Not at or within 20 metres of junction	1.38	0.00	3.97	3.06	5.17
	Roundabout with Automatic traffic signal	0.65	0.02	1.91	1.09	3.33

	Roundabout with Give way or uncontrolled	0.56	0.00	1.74	1.25	2.42
	Slip Road with Give way or uncontrolled	1.44	0.00	4.20	2.27	7.79
	T or staggered junction with Give way or uncontrolled	0.50	0.00	1.65	1.29	2.13
	T or staggered junction with Stop sign	0.91	0.03	2.49	1.12	5.52
	Using private with give way or uncontrolled	0				
Vehicle Manoeuvre	Changing lane to right/left	-1.17	0.04	0.31	0.10	0.92
	Overtaking moving vehicle	-1.15	0.04	0.32	0.10	0.97
	Overtaking stationary vehicle	-1.13	0.04	0.32	0.11	0.97
	Turning right	-1.16	0.03	0.32	0.11	0.89
	Waiting	0				
Junction location of vehicle	Approaching junction	0.33	0.00	1.38	1.22	1.57
	Cleared junction	0.43	0.00	1.54	1.28	1.85
	Entering main road	0.28	0.00	1.32	1.15	1.51
	Straight road	0				

where R_{HL} = Change in the road hierarchy level, L_B = Lower bound, and U_B = upper bound confidence interval.

The difference in road hierarchy level and the infrastructure parameters are correlated at 95% significance, except for no change in the road hierarchy (R_{HL}= 0) and a slight change in the hierarchy level from just one higher to a lower level (R_{HL}= -1). A negative relationship exists between the road type and R_{HL}. At 95% statistical significance, both dual carriageway and slip road are negatively associated with R_{HL}. On a dual carriageway, the probability of a crash decreases by 44% as R_{HL} changes from negative to positive. Similarly, in comparable circumstances, the crash probability of a slip road decreases by 30%. As a result, we can conclude that the road types of dual carriageway and slip road are safer for cyclists when R_{HL} is negative. The higher the level of change in the hierarchy, the safer (relatively) these two infrastructure types are. The junction type and control are positively associated with R_{HL} at 95 per cent statistical significance. As a result, we can conclude that as the junction's complexity grows and the road hierarchy level shifts, this becomes a possible hotspot.

A negative relationship exists between R_{HL} and vehicle manoeuvre. As the vehicle manoeuvre progresses from a simple turning lane to overtaking and turning right, the rider safety decreases as the R_{HL} switches from negative to positive. With a single adjustment in the hierarchy level, every degree of complexity increases in the movement that a cyclist is required to undertake diminishes safety by 3.2 times (1/0.31 = 3.2). As a result, while developing cycling infrastructure, extra attention should be given to prevent circumstances in which a cyclist is forced to conduct a tricky manoeuvre when there is a sudden shift in the road hierarchy, especially if the cyclist is forced to go from a lower hierarchy type to a higher hierarchy type. In such a case, the speed limit would indeed alter, placing extra pressure on the cyclist to keep up with the usual traffic flow, and automobiles would almost surely accelerate unexpectedly, negatively damaging their encounter with the bicycle. Because of the relatively enormous size of cars, this can also result in a gust of air pressure, which is significantly higher while interacting with larger vehicles. The literature is replete with examples of these forms of interactions. The English and Wales model (Guthrie, Davies, D and Gardner, 2001) found that the intensity of traffic flow is negatively linked with bicycle commuting. Similarly, the perception-based study on cycling safety (Bill, Rowe and Ferguson, 2015) found that the most critical factors considered by the cyclist to result in a crash are larger vehicle overtaking too closely, cars overtaking too closely, and their interaction with large vehicles. The majority of these findings are focused on questionnaire surveys, wherein the results have not been mathematically validated. It will be challenging to influence practitioners and policymakers before such a mathematical validation is carried out.

A positive relationship exists between the junction location of the vehicle and R_{HL}. When R_{HL} shifts from negative to positive, the safest junction position is entering the main road, followed by approaching the junction, and clearing the junction becomes the riskiest junction location. As a result, when the road hierarchical level is reduced by one level, the likelihood of a crash at an approaching intersection increases by 1.4 times, clearing the junction by 1.5 times and entering the main road by 1.3 times compared to the straight path. Exiting the intersection is 1.2 (1.54/1.38 = 1.2) times riskier than entering the intersection for each degree of change in the RHL from negative to positive.

The goal of junction design (see (DMRB TD9/93, 1993; Highways England, 2016)) is to move vehicles out of the intersection as rapidly as feasible to maximise handling abilities. For example, the exit radius is greater than the entering radius to allow cars to escape more rapidly. As a result, drivers may speed quickly and without concern for this vulnerable road user, negatively influencing the motorist-cyclist relationship. These findings must be considered when developing and planning cycling infrastructure. As we move closer to autonomous cars and infrastructure, these findings can be conveniently included in motorist-cyclist interaction algorithms. If the UN Sustainable Development Goal of halving road fatalities by 2030 are to be met, it is essential to design and build forgiving infrastructure. Making such a shift in modelling and using such approaches can help to realise the zero fatality vision.

8.6. Chapter Summary

In this chapter, an intelligent hybrid modelling paradigm is developed that can construct accurate predictive models, estimate each input variable's effect, evaluate the combined effect of the independent safety criteria, and quantify the impact of each input safety performance function. There are four predictive infrastructure models constructed with high precision (86-95%). It is established that unfavourable weather conditions and different traffic flow regimes hinder cyclist experiences, which has a wide range of negative safety implications for various facilities. The riskiest vehicle manoeuvres and the riskiest position inside the intersection are closely correlated and greatly influenced by the rider age and gender, and traffic flow conditions. As a result, these are complex variables that should be modelled for network planning and design. The exploratory data analysis concluded that the infrastructure variables pose different risks to which riders of different ages react differently. The riskiest environmental conditions are exacerbated by the prevailing traffic flow regime, posing a significant safety risk to cyclists. The traffic flow regime poses differing levels of risk to cyclists, with different genders reacting accordingly. The traffic flow conditions and infrastructure variables alone are crucial variables impacting cycling safety. As the junction's complexity grows and the road hierarchy level shifts, this becomes a possible hotspot. These findings must be considered when developing and planning cycling infrastructure.

Chapter 9.

Conclusion and Further Research

9.1. Conclusion

This thesis has investigated and modelled the critical variables affecting the cycling safety in its natural, built road environment. This is achieved by developing a novel methodological framework consisting of descriptive, statistical, artificial intelligence and mathematical approaches. The framework is applied as a case study on Tyne and Wear in northeast of England. In this process, thirteen accurate predictive safety deep learning crash models are constructed to predict the safety based upon the rider age, gender, environmental conditions, and micro infrastructure variables in its route. Simultaneously, an in-depth knowledge of how different variables (individually and combined), affect cyclist safety is identified, modelled, and quantified. In the study, a novel infrastructure variable, i.e., 'road hierarchy level and direction', is introduced, that is found to be critical safety variable. It is recommended that this variable is considered in cycling infrastructure planning and network design. The following main conclusions are deduced from the study:

a) The variables of age, gender, varied environmental conditions, and micro-infrastructure variable are critical variables affecting the safe usage of infrastructure. These variables, both individually and in combination, impact cyclist safety, emphasising the importance of including them in cyclist modelling.

b) The same infrastructure can offer varying safety depending upon the rider attributes, environmental, and flow conditions.

c) The cyclist's risk decreases with age; riders under the age of 17 are 23 times more likely to be involved in a crash than the age group of 50-59 for the same distance traversed. The elderly riders are at a slightly higher risk; riders belonging to greater than 59 age group face 1.1 higher risks than the safest age group of 50-59. This is attributed to the physical and cognitive limitations in the advanced age group. As a result, it is suggested that measures such as cycling training and handbook be explored.

d) Males face a higher risk than women for the same distance traversed (3.9 times higher). The risk for males and females is highest in their youth (0-16), 40 times and 16 times higher than the safest age group, and older women are at relatively higher risk.

e) Cycling safety is a dynamic variable that varies temporally and spatially. The spatial and environmental variables have a significantly varied effect on safety depending upon the rider personal attribute. Men are susceptible to their journey purpose, meteorological conditions, whereas females are more susceptible to externalities such as traffic flow regime. Similarly, lighting conditions have a more pronounced impact on females. There are certain features of the infrastructure which are risky for all cyclists. However, the level of risk that each infrastructure presents is dependent upon the gender of the cyclist.

f) The unsafeness of the interaction between user and infrastructure is dependent upon lighting and road surface meteorological conditions. Different environmental conditions pose different risks for different types of infrastructure.

g) The environmental conditions significantly affect the interactions in which the rider needs to undertake specific manoeuvres due to a sudden change in the road hierarchy. The change in road hierarchy and direction of change (i.e., from a higher hierarchical functional infrastructure type to a smaller one or vice versa) impacts the safety interactions.

h) As the number of safety variables that the cyclist must conform to grows, so does the risk. The riskiest vehicle manoeuvres and the riskiest position inside the intersection are closely correlated and greatly influenced by the rider age, gender, and traffic flow conditions. The riskiest environmental conditions are exacerbated by the prevailing traffic flow regime, posing a significant safety risk to cyclists.

i) The modelling requirement of a cyclist is significantly different from motorists. The traditional methods cannot be used to model a cyclist. A hybrid intelligent modelling paradigm is required, which combines different mathematical, statistical, and artificial intelligence approaches, as demonstrated in this research.

j) The present need for cyclist safety modelling is to shift to nanoscopic modelling. The future modelling should aspire to develop accurate predictive models while developing an understanding of the variable interaction.

9.2. Limitations

The study uses the crash database based upon the reported crashes. However, there may be underreporting, especially concerning single cyclist slight crashes. In contrast, severe and fatal crashes are almost certainly reported due to the nature of the injury sustained. However, there are very few alternatives to using the crash database. Other methods have been explored, such as naturalistic study (see (Walker, 2007; Dozza and Fernandez, 2014)). These methods are still in infancy, as their results cannot be quantified in terms of lives saved or disruptions to the transportation network. Another explored methodology involves using hospital data; however, such data cannot be further linked to the exact infrastructure location, time of the crash, and the prevalent traffic flow regime. The primary motivation for using the crash database is the ability to quantify the results and establish confidence for the policy implications and further use of knowledge-driven measures by road safety professionals.

9.3. Policy implications and application

This study offers scientific evidence-based recommendations for policymakers. The present modelling in road safety modelling needs to move from the simple probability-based models to deep learning neural models, which can open up new possibilities, as demonstrated in this work. The study results can significantly impact the route choice, modelling, and planning of infrastructure. The constructed models can assess with certainty regarding the infrastructure required to increase safety based upon the intended users rather than a generalised approach. This can be even employed to an infrastructure still in its planning/design phase, considering the rider's vulnerability and its susceptibility to externalities. A shift in the road safety analysis towards nanoscopic modelling can help achieve zero-vision road traffic fatality. The research reinforces a need for planning and design of infrastructure to move towards a more holistic approach while considering the limitations of this vulnerable road user. The result can contribute towards improving road safety and lead to the development of a sustainable integrated cycling transportation system. It is hoped that this research will help reduce cyclist crashes, thereby contributing to the promotion of this travel mode.

An increase in cycling mode share is required to achieve transportation system sustainability. According to the research, the risk varies substantially depending on the rider characteristics. As a result, the impact of providing additional support and training to certain road users of a given age and gender should be explored. This can address the real as well as perceived risk, which can encourage en masse cycling culture. Benefits such as tax credits, in conjunction with extra training, might also be investigated. It has been demonstrated that adverse environmental conditions have a detrimental impact on a cyclist's safety. As a result, solutions such as free (or discounted) public transportation for cyclists under such severe circumstances should be investigated. This can result in an integrated sustainable transportation system in which all transportation systems strive to deliver mobility as a service.

The widespread usage of navigation systems has paved the way for intensive use of technology in the daily travel, augmented by possible car and infrastructure automation. As a result, the potential of real-time intelligent route choice modelling for a bicycle, choosing the safest route for a given journey for a specific cyclist, is now being explored. Choosing the safest route from the route set can result in selecting the safest route based on a rider attribute, prevalent traffic flow regime, and environmental conditions using a specific optimisation algorithm. However, this concept is only in its early stages, with the anticipated improvement in the transportation landscape due to the adoption of autonomous vehicles and a boost to artificial intelligence to handle the infrastructure. As a result, it is high time that this is integrated into route and mode choice modelling. The current need is to undertake a transition to a cyclist focussed dynamic road safety model, increasing safety, and providing more focused and knowledge-driven recommendation measures.

9.4. Recommendation for further research

Whilst this study has successfully contributed to new knowledge, the results suggest several recommendations for further research.

a) Understanding the pre-crash scenarios and how personal attributes affect the handling of pre-crash and near-crash scenarios needs to be investigated. Further research should aim to quantify the pre-crash and near-crash scenarios.
b) The outputs in the predictive models (age, gender, environmental conditions, and micro-infrastructure variables) may be correlated with many underlying factors. Future research should aim to create a heterogeneous model, which can uncover the underlying variables.
c) Comparatively, the analysis should be carried out to include different countries in the analysis. This will provide a better understanding of how identified variables vary from one place to another in their contribution to the riskiness of a scenario.
d) Given that this research has shown that safety varies for different road users, the effect of cycling training should be modelled.
e) A simulator-based study should be carried to investigate the physiological and cognitive abilities that lead to the variation of risk based upon age and gender.

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Appendices

Appendix A: Yearly Cyclist flow

Hour Ending	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	12	F13	F14	F15	F16	F17	F18	F19	F20	F21	F22	F23	F24	FTotal
Mon 1 Jan	29	18	13	10	9	18	15	39	61	116	140	164	217	232	209	210	124	122	93	92	66	64	31	17	2109
Tue 2 Jan	8	10	10	67	16	38	85	200	297	199	181	170	137	171	198	200	293	354	204	123	58	62	42	21	3144
Wed 3 Jan	16	2	3	4	8	24	93	205	321	171	186	229	274	269	263	243	338	515	241	150	107	74	51	19	3806
Thu 4 Jan	21	6	7	7	19	42	118	290	330	215	141	128	184	152	165	195	300	416	251	120	100	64	49	17	3337
Fri 5 Jan	16	15	4	1	16	53	112	290	348	226	228	288	368	336	403	374	399	494	265	176	97	75	105	45	4734
Sat 6 Jan	35	14	13	12	15	37	38	78	112	157	165	242	278	325	327	327	217	226	195	191	139	134	59	25	3361
Sun 7 Jan	16	13	6	9	9	16	22	47	93	173	246	318	434	320	334	291	263	244	192	171	137	85	54	17	3510
Mon 8 Jan	14	5	5	4	25	66	149	290	379	218	184	187	263	285	316	363	477	586	339	204	131	107	67	42	4706
Tue 9 Jan	22	15	6	7	40	79	209	393	550	312	220	263	223	243	287	331	432	570	334	212	150	90	85	40	5113
Wed 10 Jan	20	14	15	11	31	73	184	420	456	291	218	207	234	235	279	379	498	604	353	222	153	79	76	49	5101
Thu 11 Jan	19	18	9	10	22	67	178	461	529	329	246	290	271	300	231	326	463	597	364	211	164	98	73	48	5324
Fri 12 Jan	25	29	16	8	40	54	229	534	541	335	338	339	336	317	355	420	491	592	346	203	139	114	86	53	5940
Sat 13 Jan	25	20	18	15	30	48	62	89	122	239	253	323	327	261	241	248	241	245	239	181	152	115	92	36	3622
Sun 14 Jan	22	26	10	8	13	25	39	61	106	197	298	400	378	324	349	272	190	202	155	242	120	66	42	30	3575
Mon 15 Jan	7	17	9	11	24	53	170	336	498	291	305	334	396	394	315	418	484	654	385	255	149	109	84	63	5761
Tue 16 Jan	13	14	10	17	34	72	176	344	445	283	245	234	228	318	349	353	487	547	372	237	159	119	72	48	5176
Wed 17 Jan	14	15	20	5	30	64	137	257	307	263	234	207	196	259	261	330	344	434	343	208	144	101	109	63	4345
Thu 18 Jan	24	17	13	17	28	36	121	189	233	198	134	192	273	309	353	347	363	384	244	180	142	83	77	46	4003
Fri 19 Jan	36	22	44	20	58	78	182	453	365	310	205	262	312	316	317	400	401	441	302	210	163	115	78	46	5136
Sat 20 Jan	30	20	28	13	32	36	61	87	146	132	186	233	299	298	308	287	287	226	196	213	159	101	65	38	3481
Sun 21 Jan	20	10	15	18	13	19	24	28	73	132	142	180	176	209	185	97	86	93	101	122	95	82	58	30	2008
Mon 22 Jan	19	11	14	14	24	53	142	244	400	336	280	295	378	443	376	357	475	583	359	272	173	145	79	47	5519
Tue 23 Jan	29	16	27	16	23	85	255	468	743	492	548	526	539	446	469	540	692	1022	571	350	266	179	234	63	8599
Wed 24 Jan	39	27	20	12	28	91	203	324	542	424	379	387	342	411	344	497	605	765	503	354	239	145	106	74	6861
Thu 25 Jan	27	22	29	20	34	104	224	461	641	532	437	488	441	527	528	525	702	818	471	290	209	147	104	83	7864
Fri 26 Jan	35	19	18	19	30	85	236	495	597	395	361	419	423	478	446	495	630	586	414	252	186	135	79	61	6894
Sat 27 Jan	36	29	27	46	34	58	94	121	221	243	340	375	475	431	383	347	318	235	230	207	137	92	67	51	4597
Sun 28 Jan	50	16	13	17	11	29	35	57	117	180	267	272	327	285	298	319	259	267	241	223	162	93	50	35	3623
Mon 29 Jan	25	16	15	14	36	89	249	539	739	488	390	391	456	486	472	523	745	953	531	305	218	175	144	75	8074
Tue 30 Jan	39	20	22	20	29	106	330	614	809	535	517	470	487	556	489	680	893	994	654	338	261	180	116	73	9232
Wed 31 Jan	37	22	15	22	27	95	274	618	825	521	327	384	448	543	429	557	748	960	646	295	231	155	174	88	8441
January Average	24.4	16.5	15.3	15.1	25.4	56.6	139	280	371	280	267	294	322	331	328	356	417	492	316	217	153	108	81.1	45.2	
Thu 1 Feb	50	61	29	31	40	97	307	616	849	560	439	399	473	432	572	597	769	953	705	387	302	173	145	109	9095
Fri 2 Feb	61	83	23	29	33	223	365	740	949	593	493	552	558	667	705	795	923	985	735	508	361	332	233	278	
Sat 3 Feb	72	52	35	42	53	103	101	114	233	307	270	324	379	362	271	345	320	279	230	186	133	106	70	61	4448
Sun 4 Feb	108	91	67	123	27	32	48	89	186	371	517	583	550	540	499	429	425	352	435	333	232	124	97	52	6310
Mon 5 Feb	27	18	15	18	27	83	267	529	769	510	409	422	416	409	459	522	829	901	532	344	270	167	115	64	8122
Tue 6 Feb	21	21	24	24	36	99	243	476	644	346	223	238	251	258	323	410	602	712	426	358	193	155	134	53	6270
Wed 7 Feb	23	20	13	13	51	73	220	450	639	457	315	340	421	460	494	462	635	743	475	278	223	151	108	103	7167
Thu 8 Feb	24	20	24	13	29	101	273	507	645	412	380	391	378	412	499	443	660	710	419	239	187	126	70	77	7039
Fri 9 Feb	49	68	56	41	61	118	378	578	612	367	329	363	411	435	563	623	681	637	394	290	213	154	118	132	7671

Sat 10 Feb	42	25	25	29	37	110	145	153	184	232	286	355	373	393	426	455	351	246	253	189	126	95	66	42	4638
Sun 11 Feb	35	19	16	28	24	46	55	95	152	317	469	477	507	467	383	347	302	276	233	209	178	119	85	59	4898
Mon 12 Feb	25	25	29	41	51	134	352	461	575	441	426	505	511	500	640	651	751	844	481	345	226	167	149	95	8425
Tue 13 Feb	57	36	31	31	49	120	332	521	534	386	295	289	348	354	359	467	636	716	423	252	158	131	126	66	6717
Wed 14 Feb	44	54	39	15	56	149	313	487	536	439	346	398	394	364	360	457	503	660	396	242	176	116	149	92	6785
Thu 15 Feb	38	22	44	23	57	137	349	525	557	500	488	479	506	492	537	586	709	808	560	328	213	154	152	98	8362
Fri 16 Feb	55	38	50	26	54	125	367	564	583	511	564	597	713	687	719	689	762	739	526	321	197	153	131	127	9298
Sat 17 Feb	43	26	25	37	43	110	149	178	237	396	419	500	642	639	712	632	505	370	325	253	170	135	95	80	6721
Sun 18 Feb	45	28	27	27	24	48	70	140	303	511	662	731	700	650	617	535	407	365	301	221	189	120	80	51	6852
Mon 19 Feb	33	21	29	23	43	128	309	595	818	510	368	305	397	382	460	520	704	887	567	309	244	204	148	102	8106
Tue 20 Feb	49	41	24	38	37	129	419	712	884	588	585	496	506	520	552	814	858	1028	656	412	285	190	154	127	
Wed 21 Feb	46	47	38	31	62	148	425	728	931	664	540	517	640	651	710	766	961	1011	648	409	288	206	181	162	
Thu 22 Feb	47	24	56	26	43	111	387	676	794	558	561	531	554	542	598	642	897	957	659	389	271	222	167	152	9864
Fri 23 Feb	50	60	47	16	46	122	339	633	757	521	448	560	531	550	612	675	678	741	435	299	256	176	134	138	8824
Sat 24 Feb	46	43	39	49	44	101	137	215	315	367	463	532	620	561	565	481	440	326	330	292	203	180	98	80	6527
Sun 25 Feb	58	37	30	43	23	46	82	118	245	466	656	575	567	642	563	511	377	354	296	286	247	151	89	40	6502
Mon 26 Feb	37	33	26	26	56	126	343	589	749	521	379	449	430	478	479	535	684	822	547	316	292	164	150	122	8353
Tue 27 Feb	72	114	30	8	35	92	189	290	318	276	214	225	250	284	287	361	435	470	388	223	152	117	93	62	4985
Wed 28 Feb	49	42	40	26	58	66	132	166	217	161	146	200	164	253	157	218	248	159	127	107	102	46	42	55	2981
February Average	46.6	41.8	33.3	31.3	42.8	106	253	427	543	439	418	440	471	478	504	535	609	645	447	297	217	155	121	95.7	
Thu 1 Mar	25	20	16	17	21	61	132	250	236	215	172	158	147	146	167	182	187	169	113	70	60	76	48	32	2720
Fri 2 Mar	25	25	20	21	22	53	96	157	158	174	137	163	195	182	167	175	194	160	116	93	71	47	47	47	2545
Sat 3 Mar	33	23	22	23	32	52	70	88	90	103	122	147	133	112	119	119	115	137	116	114	81	69	56	37	2013
Sun 4 Mar	27	21	7	16	23	35	22	24	43	55	90	91	73	85	80	85	105	124	105	94	112	88	76	61	1542
Mon 5 Mar	20	25	17	10	21	78	178	388	576	416	277	369	351	339	430	503	632	862	519	282	199	167	124	82	6865
Tue 6 Mar	38	40	39	19	31	101	203	449	554	348	245	267	321	364	385	497	620	738	517	345	224	213	163	114	6835
Wed 7 Mar	52	52	52	23	55	129	396	757	818	567	525	522	550	557	596	641	919	1079	673	408	297	217	215	155	
Thu 8 Mar	74	47	58	39	42	130	394	731	755	567	460	488	536	538	502	638	932	983	636	385	262	205	223	152	9777
Fri 9 Mar	65	73	72	54	49	136	440	721	900	585	524	640	682	628	753	870	864	887	536	323	263	231	169	156	
Sat 10 Mar	57	39	37	30	30	104	142	159	192	202	259	280	282	378	351	397	318	308	258	204	169	126	86	66	4474
Sun 11 Mar	53	30	14	40	24	70	100	156	369	528	699	734	684	593	622	605	477	473	333	237	233	177	124	92	7467
Mon 12 Mar	57	33	39	43	53	174	442	795	1041	632	466	384	453	399	462	647	905	1035	596	346	257	194	196	160	9809
Tue 13 Mar	71	54	61	47	74	179	551	899	1082	721	629	608	656	650	724	877	1015	1215	797	459	334	253	240	144	
Wed 14 Mar	104	80	59	51	72	166	582	969	1261	749	706	622	728	661	669	928	1068	1232	777	473	300	228	228	191	
Thu 15 Mar	78	62	62	66	59	166	494	787	979	661	411	453	436	394	400	584	765	790	527	294	234	182	132	117	9133
Fri 16 Mar	62	65	48	36	50	126	291	460	580	386	328	343	372	407	421	449	516	522	386	302	207	168	126	136	6787
Sat 17 Mar	32	26	28	39	52	89	128	116	170	193	220	247	300	277	280	249	235	225	166	155	113	120	84	46	3590
Sun 18 Mar	21	34	29	29	33	38	52	46	61	98	140	127	144	126	146	161	146	127	130	138	135	88	92	47	2188
Mon 19 Mar	43	41	92	97	92	113	352	724	788	501	397	415	382	437	509	527	699	682	465	284	251	177	177	135	8380
Tue 20 Mar	49	63	40	29	54	135	451	744	976	596	563	582	591	648	653	776	976	1164	698	394	298	247	189	136	####
Wed 21 Mar	70	43	75	51	69	146	529	811	1052	646	545	558	571	531	542	642	899	1095	623	369	252	167	180	135	####
Thu 22 Mar	65	38	66	28	76	154	472	825	910	651	611	594	611	676	698	782	996	1165	712	439	312	222	191	157	####
Fri 23 Mar	53	71	34	57	205	291	430	718	1012	649	552	552	542	545	725	830	925	981	629	552	334	247	232	192	####
Sat 24 Mar	84	139	72	40	43	132	210	314	394	598	732	740	790	870	756	716	629	586	407	260	241	147	103	71	9074
Sun 25 Mar	56	0	39	92	90	52	94	162	335	584	879	945	929	936	978	828	712	597	396	322	273	171	114	108	9692
Mon 26 Mar	38	63	38	33	99	181	515	834	1105	874	641	680	753	742	870	892	1066	1406	987	598	348	262	221	174	####
Tue 27 Mar	141	53	49	24	59	164	398	713	1078	554	462	407	423	451	513	704	852	998	713	451	313	279	196	155	####

Wed 28 Mar	66	95	43	37	130	337	570	918	1213	757	579	744	590	630	583	788	926	1232	895	483	392	258	213	169	####
Thu 29 Mar	108	78	62	61	112	191	430	787	1003	712	775	813	771	796	903	966	1082	1163	767	615	528	339	263	287	####
Fri 30 Mar	72	73	34	20	25	64	108	151	213	287	380	434	383	485	456	401	405	406	350	223	175	193	110	69	5517
Sat 31 Mar	50	36	36	32	30	68	91	147	202	228	206	225	258	259	223	286	247	226	228	134	140	115	76	64	3607
March Average	57.7	49.7	43.9	38.8	58.9	126	302	510	650	479	443	462	472	479	506	572	659	734	489	318	239	183	151	119	####
Sun 1 Apr	44	27	22	23	34	45	52	93	235	427	561	619	671	501	467	470	392	354	305	183	146	151	125	110	6057
Mon 2 Apr	44	18	30	17	29	45	79	99	128	124	123	127	168	144	167	191	143	173	199	191	125	91	104	47	2606
Tue 3 Apr	66	31	32	26	52	136	379	634	729	529	431	437	433	446	486	536	748	961	616	401	333	241	265	163	9111
Wed 4 Apr	61	57	29	36	50	122	426	692	658	396	373	353	382	482	693	539	710	829	419	272	135	118	127	125	8084
Thu 5 Apr	26	15	9	93	27	63	149	291	316	295	307	477	400	441	373	380	489	595	411	266	141	121	54	46	5785
Fri 6 Apr	28	26	10	19	63	76	189	375	331	288	295	298	362	355	342	376	362	425	250	184	112	92	64	48	4970
Sat 7 Apr	31	17	10	12	36	49	75	135	241	246	293	302	283	216	169	129	133	110	104	70	61	59	37	29	2847
Sun 8 Apr	21	11	7	11	11	17	69	101	235	359	421	477	469	501	492	453	342	311	240	182	109	66	41	42	4988
Mon 9 Apr	22	5	7	12	28	101	227	424	404	352	385	430	425	402	403	456	565	702	446	293	173	88	64	51	6465
Tue 10 Apr	18	14	14	11	29	62	117	227	189	135	109	80	101	104	125	141	207	211	166	93	70	61	35	35	2354
Wed 11 Apr	23	16	34	34	69	70	161	238	243	197	169	184	230	193	229	230	351	358	227	149	80	64	43	32	3624
Thu 12 Apr	20	11	15	16	30	74	174	289	268	188	235	169	187	190	165	190	250	259	179	124	63	55	44	27	3222
Fri 13 Apr	17	11	18	8	20	50	121	191	195	140	150	149	233	236	209	231	257	222	188	130	80	74	32	43	3005
Sat 14 Apr	27	14	9	11	26	47	84	150	224	258	349	379	372	305	344	328	267	208	203	145	83	70	42	29	3974
Sun 15 Apr	33	16	10	13	9	31	41	119	270	401	569	491	427	415	391	345	329	228	136	97	79	59	30	15	4554
Mon 16 Apr	11	14	15	12	26	94	211	395	427	325	335	297	301	343	331	359	478	562	375	230	111	87	92	42	5473
Tue 17 Apr	18	18	14	9	28	98	227	408	485	298	285	291	237	244	282	317	461	456	378	243	137	121	61	34	5150
Wed 18 Apr	32	21	20	17	30	102	233	475	550	341	332	316	321	350	350	416	550	663	464	320	195	106	63	37	6304
Thu 19 Apr	25	21	19	9	26	70	212	434	494	333	369	396	340	401	422	426	543	596	444	307	200	98	53	28	6266
Fri 20 Apr	86	84	48	46	65	198	622	1080	1401	906	765	767	917	963	1067	1184	1400	1323	923	689	482	327	218	211	####
Sat 21 Apr	102	98	69	40	50	147	234	430	627	754	911	1039	1054	1050	1029	902	813	743	577	462	381	307	154	179	####
Sun 22 Apr	73	58	77	36	36	70	153	328	541	840	842	719	619	517	803	696	684	603	540	474	350	273	186	110	9628
Mon 23 Apr	59	45	44	41	50	216	643	1101	1551	962	687	620	699	823	803	981	1323	1703	1084	643	433	275	276	205	####
Tue 24 Apr	77	62	38	41	57	211	651	1181	1537	934	796	657	808	772	734	913	1250	1477	942	535	328	242	246	179	####
Wed 25 Apr	99	75	56	46	64	211	586	1100	1442	921	679	777	744	824	817	964	1366	1563	1120	768	495	360	324	220	####
Thu 26 Apr	92	73	65	36	69	181	589	1028	1329	841	609	562	646	683	648	939	1301	1430	982	718	445	362	304	234	####
Fri 27 Apr	113	97	79	64	67	186	547	1020	1325	992	842	801	792	866	1018	1018	1192	1342	910	605	500	325	263	220	####
Sat 28 Apr	77	63	58	41	53	102	203	329	526	564	713	821	816	749	740	613	526	550	505	458	256	253	175	112	9303
Sun 29 Apr	86	38	41	30	32	62	146	256	468	702	841	925	862	825	787	808	787	725	661	488	400	219	174	113	####
Mon 30 Apr	75	56	48	33	67	185	529	1134	1368	811	610	606	678	680	648	906	1209	1598	1093	666	438	291	246	197	####
April Average	50.2	37.1	31.6	28.1	41.1	104	271	492	625	495	480	486	499	501	518	548	648	709	503	346	231	169	131	98.8	####
Tue 1 May	70	63	51	32	56	221	681	1259	1529	1019	851	834	699	784	826	987	1458	1759	1173	764	470	380	229	220	####
Wed 2 May	69	100	48	51	60	167	502	1002	1309	820	553	566	598	627	714	925	1175	1457	986	721	421	295	269	216	####
Thu 3 May	123	79	38	36	59	161	595	1084	1277	943	831	621	740	683	728	879	1389	1401	1015	612	410	314	242	215	####
Fri 4 May	69	73	45	43	64	167	564	921	1097	791	650	710	742	876	1019	1011	1172	1206	841	651	452	357	220	272	####
Sat 5 May	102	64	51	46	39	114	274	359	607	711	1009	980	983	983	981	938	708	712	596	488	337	226	189	142	####
Sun 6 May	81	52	45	38	21	63	158	301	629	824	977	960	931	986	951	803	847	710	661	497	367	262	183	128	####
Mon 7 May	79	66	63	37	36	82	176	384	622	918	992	1141	1235	1264	1129	1042	1000	866	758	618	465	346	264	136	####
Tue 8 May	94	77	66	54	67	188	718	1236	1509	1011	847	835	877	938	951	1086	1444	1620	949	619	403	339	280	239	####
Wed 9 May	100	93	51	43	50	263	751	1246	1381	928	693	710	684	697	868	1031	1372	1638	989	573	393	315	266	194	####
Thu 10 May	94	80	37	27	55	195	560	1100	1368	826	690	686	704	693	789	1025	1332	1567	1207	804	562	364	297	242	####

Fri 11 May	114	71	64	45	66	193	622	1129	1281	893	723	759	838	807	852	1056	1180	1304	766	661	442	318	295	206	####
Sat 12 May	81	42	52	69	57	134	233	345	578	766	898	969	1054	984	1080	1003	880	736	586	456	339	234	173	140	####
Sun 13 May	90	68	46	34	23	58	93	158	287	541	626	645	721	875	862	745	746	793	782	535	464	280	201	114	9787
Mon 14 May	75	72	36	50	61	185	707	1205	1500	1034	847	890	804	937	954	1244	1527	1938	1375	960	599	393	322	227	####
Tue 15 May	98	93	29	30	75	234	784	1371	1621	1071	846	793	856	940	909	1165	1623	1969	1376	975	616	390	326	286	####
Wed 16 May	73	60	47	50	69	193	664	1162	1480	791	595	606	664	631	717	1015	1327	1661	1188	762	544	367	302	221	####
Thu 17 May	54	38	24	31	44	95	323	493	510	354	325	305	316	355	430	439	580	643	466	348	236	152	105	86	6752
Fri 18 May	34	43	21	24	34	94	310	459	527	397	344	416	425	401	452	567	483	525	383	295	168	148	104	92	6746
Sat 19 May	33	38	25	23	26	91	127	199	324	441	457	557	568	503	539	491	404	327	262	217	176	126	101	61	6116
Sun 20 May	45	33	31	20	12	47	97	209	339	498	574	560	522	523	623	534	449	436	346	243	188	115	73	41	6558
Mon 21 May	36	28	18	17	37	102	309	466	513	369	380	363	393	451	403	501	647	721	584	348	240	167	124	105	7322
Tue 22 May	42	21	23	22	34	88	253	372	370	236	203	190	269	268	255	326	435	498	422	259	174	106	106	86	5058
Wed 23 May	106	46	16	26	28	106	285	420	492	303	336	324	262	285	332	400	491	548	460	285	183	139	106	98	6077
Thu 24 May	41	20	24	23	29	87	290	406	455	323	316	309	280	327	382	448	490	536	405	274	187	116	116	82	5966
Fri 25 May	33	42	20	25	30	91	242	386	380	325	274	319	298	335	340	367	320	288	201	144	128	89	80	84	4841
Sat 26 May	21	23	15	15	26	72	98	153	233	305	338	378	369	406	378	369	334	272	250	205	115	81	90	50	4596
Sun 27 May	20	25	7	11	13	47	76	153	264	446	497	507	448	472	478	438	447	342	303	215	137	122	57	52	5577
Mon 28 May	31	12	13	23	24	57	73	132	230	319	422	471	497	518	601	546	483	371	277	218	157	125	89	62	5751
Tue 29 May	29	23	12	12	21	81	198	343	320	293	250	262	286	300	319	347	422	540	367	243	181	110	80	60	5099
Wed 30 May	17	22	14	19	28	60	212	328	356	263	238	266	279	264	277	336	449	494	344	235	163	95	81	36	4876
Thu 31 May	32	20	20	14	31	61	197	329	363	280	337	296	339	380	392	389	496	610	490	334	234	145	79	66	5934
May Average	64.1	51.2	33.9	31.9	41.1	122	360	616	766	614	578	588	603	629	662	724	842	919	671	470	321	226	176	137	####
Fri 1 Jun	97	112	62	43	78	198	590	1033	1132	839	866	865	935	1035	1137	1122	1240	1287	1010	743	542	418	303	239	####
Sat 2 Jun	130	81	61	61	59	168	230	390	601	701	775	768	881	870	846	771	719	614	444	351	246	212	134	99	####
Sun 3 Jun	81	68	35	119	97	105	190	224	439	572	786	762	824	745	728	835	712	740	559	420	424	243	179	129	####
Mon 4 Jun	65	63	54	121	61	192	615	993	1238	750	687	683	696	752	871	1047	1329	1553	1077	688	433	336	276	213	####
Tue 5 Jun	100	94	74	35	68	261	699	1265	1556	832	823	767	794	968	961	1133	1577	1899	1398	889	540	424	301	233	####
Wed 6 Jun	98	96	37	50	75	263	725	1139	1407	948	704	616	795	737	864	1081	1308	1700	1281	876	505	377	273	177	####
Thu 7 Jun	86	81	57	36	77	252	711	1310	1432	934	730	756	826	893	933	1159	1404	1720	1209	776	526	398	299	205	####
Fri 8 Jun	95	85	40	49	75	244	669	1141	1281	829	746	776	832	846	937	1127	1199	1336	904	630	406	320	282	253	####
Sat 9 Jun	235	125	123	51	74	192	247	415	709	738	775	827	902	879	939	830	985	801	652	429	331	288	172	145	####
Sun 10 Jun	91	79	75	77	48	183	178	372	575	822	969	1135	1274	1099	1066	1027	791	609	528	373	385	273	170	133	####
Mon 11 Jun	115	56	59	109	126	302	693	1325	1568	866	777	771	783	825	883	991	1516	1795	1079	689	479	276	262	164	####
Tue 12 Jun	106	69	49	47	125	254	785	1429	1520	988	793	765	792	857	968	1066	1412	1860	1268	731	499	377	288	245	####
Wed 13 Jun	96	92	58	89	166	312	765	1310	1498	959	765	794	849	815	880	1163	1407	1700	1107	623	412	338	245	163	####
Thu 14 Jun	79	67	45	29	66	169	497	843	881	565	427	434	400	477	542	743	918	896	711	507	414	313	247	170	####
Fri 15 Jun	105	97	90	91	85	200	634	1122	1183	882	792	742	776	883	1026	1015	1198	1206	845	481	361	328	219	182	####
Sat 16 Jun	73	55	43	38	48	103	255	368	443	538	636	677	693	744	645	680	494	488	483	419	324	187	139	104	8677
Sun 17 Jun	94	40	36	36	36	92	203	294	622	804	1098	1320	1235	1131	1038	907	749	578	483	362	274	181	148	115	####
Mon 18 Jun	88	127	61	102	64	220	700	1162	1403	946	782	677	716	758	819	1117	1463	1727	919	509	344	378	250	204	####
Tue 19 Jun	49	74	43	173	172	246	811	1381	1560	911	762	705	807	806	877	1125	1345	1902	1236	700	391	312	250	174	####
Wed 20 Jun	92	110	63	46	69	224	582	1167	1268	798	569	595	544	620	679	932	1246	1522	1024	653	387	284	288	219	####
Thu 21 Jun	94	88	165	146	153	302	921	1360	1559	1048	829	798	820	918	847	1179	1367	1738	1210	791	514	378	262	231	####
Fri 22 Jun	138	120	36	50	67	215	705	1302	1481	1038	957	959	1020	1080	1157	1312	1522	1465	1050	691	522	362	257	260	####
Sat 23 Jun	108	130	90	141	63	182	304	414	645	731	820	896	1038	960	1088	864	833	684	605	477	326	241	216	121	####
Sun 24 Jun	110	68	60	140	48	113	200	358	711	935	1090	1151	1099	931	848	886	1000	823	692	542	478	318	231	129	####
Mon 25 Jun	84	57	59	86	107	231	763	1289	1585	1079	922	848	935	911	984	1178	1538	1932	1294	887	536	412	261	231	####

Tue 26 Jun	47	81	44	137	80	255	786	1463	1524	1001	821	861	945	921	1029	1167	1686	2095	1386	939	527	341	267	225	####
Wed 27 Jun	78	79	25	41	71	264	826	1349	1552	944	890	877	950	898	1017	1280	1505	1857	1434	909	578	508	319	247	####
Thu 28 Jun	103	105	50	96	109	234	753	1338	1609	985	938	941	931	1001	1003	1240	1474	1706	1149	696	406	403	342	214	####
Fri 29 Jun	93	75	84	48	82	225	668	1123	1332	941	891	829	807	1055	1041	1524	1295	1300	840	541	439	354	256	186	####
Sat 30 Jun	74	129	88	53	60	146	232	337	555	719	771	992	1011	1025	974	869	853	725	583	425	366	256	196	124	####
June Average	96.8	86.8	62.2	78	83.6	212	565	967	1162	855	806	820	864	881	921	1046	1203	1342	949	625	431	328	244	184	####
Sun 1 Jul	89	58	33	34	43	85	202	350	606	789	920	1216	1087	1194	1061	1011	896	730	611	469	326	247	210	117	####
Mon 2 Jul	46	45	64	57	70	211	687	1261	1599	950	774	803	815	853	851	1049	1421	1843	1237	764	482	359	244	163	####
Tue 3 Jul	69	65	156	100	139	264	830	1275	1530	869	843	835	877	842	916	1127	1572	1898	1122	600	336	318	434	240	####
Wed 4 Jul	124	108	58	42	77	199	728	1296	1500	851	728	684	753	750	893	1198	1493	1939	1237	834	526	371	303	192	####
Thu 5 Jul	80	87	77	44	54	217	766	1330	1535	959	828	862	764	835	824	1245	1386	1779	1266	754	495	349	270	228	####
Fri 6 Jul	87	85	61	45	68	189	627	1249	1376	875	839	863	826	1007	1169	1331	1275	1458	916	684	491	337	254	250	####
Sat 7 Jul	92	105	45	73	85	185	336	431	681	825	886	910	866	831	761	529	418	636	601	501	360	299	193	130	####
Sun 8 Jul	136	101	51	42	41	112	179	372	573	955	962	961	905	912	884	779	739	680	636	454	354	217	155	99	####
Mon 9 Jul	68	45	38	20	51	231	622	1165	1465	848	663	670	581	671	750	902	1387	1718	1151	694	485	320	248	166	####
Tue 10 Jul	75	73	57	31	62	274	747	1360	1603	942	694	784	787	886	820	1231	1609	2174	1468	774	521	373	316	229	####
Wed 11 Jul	100	86	67	28	59	239	748	1303	1429	1001	713	856	831	903	926	1209	1547	1721	1084	508	267	293	379	226	####
Thu 12 Jul	99	78	71	57	58	197	636	1074	1406	869	739	780	767	782	902	1045	1296	1618	1225	757	531	368	308	201	####
Fri 13 Jul	95	90	43	45	54	242	607	1157	1301	893	718	826	843	890	1038	1295	1259	1316	908	628	476	370	263	216	####
Sat 14 Jul	158	81	94	73	46	153	235	429	729	722	873	981	1037	1062	970	799	785	719	671	554	408	309	207	125	####
Sun 15 Jul	75	53	49	36	20	80	158	314	615	754	937	1023	1071	1022	960	875	769	621	661	557	449	246	175	98	####
Mon 16 Jul	59	34	28	39	47	206	659	1092	1348	887	674	696	591	533	540	778	1135	1331	947	547	420	263	265	166	####
Tue 17 Jul	61	40	63	38	42	178	617	1180	1554	944	800	711	668	675	782	1010	1258	1639	1168	773	506	343	264	225	####
Wed 18 Jul	74	51	45	44	55	243	764	1257	1577	1046	829	876	911	854	849	1166	1700	1851	1219	726	532	330	267	212	####
Thu 19 Jul	84	95	72	35	72	226	751	1297	1633	944	891	875	887	878	981	1265	1538	1914	1254	860	615	371	360	259	####
Fri 20 Jul	122	79	63	132	124	273	634	1142	1303	929	714	765	765	791	798	752	1016	1129	706	435	357	277	206	208	####
Sat 21 Jul	109	66	46	37	59	131	263	377	539	716	828	909	898	841	830	885	756	726	599	473	336	265	177	146	####
Sun 22 Jul	83	63	52	21	45	92	209	359	598	760	1113	995	1061	983	1065	928	829	820	692	498	370	262	148	99	####
Mon 23 Jul	46	29	14	27	60	178	582	1012	1297	881	764	844	880	858	870	977	1350	1721	1125	708	418	296	192	109	####
Tue 24 Jul	52	30	20	21	39	187	705	1101	1255	884	802	779	781	829	821	903	1369	1732	1137	780	520	336	186	141	####
Wed 25 Jul	48	41	30	12	58	188	589	1125	1496	954	946	940	965	950	1052	1106	1563	1949	1377	902	686	421	239	156	####
Thu 26 Jul	64	42	31	25	53	196	553	1107	1354	980	848	891	931	900	1023	1159	1433	1736	1183	730	571	355	222	138	####
Fri 27 Jul	73	100	42	26	66	161	481	942	1094	817	662	611	640	768	829	850	1003	1091	760	556	383	200	152	131	####
Sat 28 Jul	45	56	32	29	46	118	176	260	433	506	492	497	614	626	688	686	588	484	371	266	252	176	112	91	7644
Sun 29 Jul	62	44	43	26	38	58	122	191	263	275	468	608	483	480	452	433	352	368	415	389	312	188	98	81	6249
Mon 30 Jul	48	33	16	20	33	186	491	997	1196	925	766	821	901	873	758	992	1431	1666	820	480	359	253	118	111	####
Tue 31 Jul	65	34	26	28	43	207	587	1100	1327	947	783	814	860	815	832	1010	1338	1780	1129	696	486	313	176	110	####
July Average	80.3	64.4	51.2	41.5	58.3	184	526	932	1168	855	790	829	827	842	868	985	1178	1380	958	624	440	304	230	163	####
Wed 1 Aug	62	27	27	22	46	183	599	1032	1196	907	762	841	824	895	906	979	1267	1455	795	470	353	259	164	116	####
Thu 2 Aug	55	27	34	27	60	190	512	1026	1202	890	768	873	898	884	910	980	1347	1609	1224	829	498	343	208	139	####
Fri 3 Aug	73	51	31	31	48	155	480	917	977	598	500	432	524	550	512	695	995	1064	699	416	360	239	149	136	####
Sat 4 Aug	83	74	83	46	56	138	219	373	562	731	773	918	887	859	866	925	772	683	550	420	337	247	150	101	####
Sun 5 Aug	92	63	43	33	37	131	180	338	559	785	945	993	1057	965	926	1000	801	707	581	483	383	224	146	95	####
Mon 6 Aug	51	35	27	25	53	216	557	925	1042	763	679	771	799	800	847	992	1350	1557	1105	745	522	308	228	188	####
Tue 7 Aug	82	66	46	32	71	203	686	1232	1389	888	890	906	896	945	1011	1097	1614	1846	1182	784	546	359	262	176	####

Wed 8 Aug	101	64	52	35	84	210	619	1114	1288	865	794	798	829	827	894	949	1268	1609	1103	776	500	329	231	209	####
Thu 9 Aug	104	75	43	40	86	225	636	1031	1192	938	823	770	817	906	952	1013	1308	1539	1077	746	503	334	291	181	####
Fri 10 Aug	93	75	47	43	59	180	563	924	1025	782	520	660	740	847	896	979	1026	1094	840	469	323	234	175	171	####
Sat 11 Aug	59	74	57	21	46	133	251	360	569	668	822	927	839	831	813	861	728	682	495	420	256	164	152	84	####
Sun 12 Aug	62	30	30	22	29	42	143	100	150	198	257	336	469	528	632	604	572	440	390	316	229	182	122	80	5963
Mon 13 Aug	54	75	22	21	58	150	346	639	822	521	457	506	553	607	650	777	887	1201	844	568	359	215	204	146	####
Tue 14 Aug	66	74	45	34	67	219	660	1041	1279	866	715	766	835	804	791	919	1259	1605	1059	633	446	297	215	149	####
Wed 15 Aug	94	78	51	36	73	207	641	1069	1216	819	795	720	719	719	870	1038	1142	1422	820	514	298	211	178	153	####
Thu 16 Aug	90	55	45	45	71	188	581	918	1114	753	680	823	762	706	825	981	1157	1556	818	637	417	281	210	170	####
Fri 17 Aug	168	95	46	51	87	262	614	907	1030	733	721	873	875	941	944	987	1093	1064	663	422	370	257	192	160	####
Sat 18 Aug	79	68	53	65	57	141	198	325	430	570	728	739	734	678	751	742	580	589	512	338	293	243	152	155	9220
Sun 19 Aug	95	74	35	29	42	64	94	186	304	411	573	632	642	598	670	781	683	554	440	329	298	186	190	107	8017
Mon 20 Aug	109	53	43	92	101	277	667	1020	1237	849	784	839	848	900	951	1029	1314	1378	956	509	331	253	203	194	####
Tue 21 Aug	87	69	36	38	75	218	707	1023	1211	821	613	721	774	800	895	1002	1260	1527	1062	757	530	331	245	194	####
Wed 22 Aug	108	69	98	114	139	327	671	1040	1140	775	663	599	667	747	683	921	1189	1481	1013	637	428	296	230	149	####
Thu 23 Aug	79	80	43	31	65	193	623	1055	1112	865	735	601	701	710	721	844	1155	1209	846	624	369	261	193	182	####
Fri 24 Aug	111	87	39	40	58	162	518	902	970	743	746	801	754	867	881	874	1021	1092	633	537	366	242	184	153	####
Sat 25 Aug	81	35	32	30	49	93	209	327	495	635	756	833	809	892	729	714	607	567	459	323	228	180	117	84	9284
Sun 26 Aug	59	50	30	22	19	47	103	233	369	437	549	440	436	478	477	380	366	252	259	235	180	144	96	59	5720
Mon 27 Aug	50	39	35	37	44	94	170	244	403	533	684	705	875	855	900	808	727	592	538	341	273	230	176	94	9447
Tue 28 Aug	60	52	43	32	44	195	566	1001	1103	835	714	715	762	826	875	1127	1286	1579	1028	691	416	267	224	155	####
Wed 29 Aug	80	73	32	49	54	172	650	1104	1093	763	652	644	680	746	840	988	1312	1574	1052	681	423	293	200	200	####
Thu 30 Aug	87	66	45	39	69	201	600	1010	1147	831	822	764	741	788	902	911	1157	1487	906	673	472	230	226	185	####
Fri 31 Aug	92	77	39	49	75	189	593	957	1157	770	728	838	841	895	1015	1078	1298	1178	757	506	408	280	195	186	####
August Average	82.8	62.3	43	39.7	62	174	473	786	928	727	698	735	761	787	824	902	1050	1167	797	543	378	255	191	147	####
Sat 1 Sep	68	67	48	52	51	147	219	420	470	650	662	717	847	743	759	767	706	596	526	394	294	186	114	120	9623
Sun 2 Sep	91	57	48	40	29	96	129	271	461	675	848	878	860	871	919	849	785	699	492	358	353	206	136	86	####
Mon 3 Sep	53	44	22	36	57	166	613	1080	1202	749	663	621	665	774	784	890	968	1285	670	448	243	184	159	111	####
Tue 4 Sep	66	68	35	41	57	215	630	1183	1389	850	666	615	704	731	805	962	1283	1625	1012	655	439	288	230	135	####
Wed 5 Sep	96	65	51	40	69	199	650	1202	1504	824	727	678	897	737	861	1105	1395	1672	1135	699	407	272	227	153	####
Thu 6 Sep	89	76	47	44	54	199	650	1236	1643	945	869	694	784	685	805	1185	1361	1469	847	488	351	243	177	148	####
Fri 7 Sep	88	74	58	35	64	221	554	990	1119	578	486	447	551	665	686	814	938	1019	693	388	335	224	167	123	####
Sat 8 Sep	72	45	46	48	45	103	214	348	480	569	684	671	705	705	633	580	514	514	509	330	286	170	138	127	8536
Sun 9 Sep	76	52	39	31	32	77	143	247	408	685	946	851	881	788	752	720	639	556	507	346	259	170	136	89	9430
Mon 10 Sep	43	81	23	19	46	194	623	1070	1428	798	620	607	646	700	755	1020	1246	1477	771	446	270	161	168	124	####
Tue 11 Sep	55	53	25	35	48	171	628	1119	1335	760	550	584	637	661	727	1023	1225	1473	1008	613	322	256	236	157	####
Wed 12 Sep	81	48	51	35	109	269	675	1232	1417	827	642	652	749	717	811	1008	1211	1565	972	566	383	256	206	140	####
Thu 13 Sep	92	85	33	34	60	199	650	1125	1519	909	668	737	667	719	769	1069	1226	1612	934	587	339	208	219	174	####
Fri 14 Sep	108	80	25	40	69	199	552	948	1378	746	584	572	599	719	861	891	928	1069	753	358	263	217	167	144	####
Sat 15 Sep	60	44	31	36	67	129	171	378	438	575	722	682	721	729	812	710	686	617	499	371	258	182	109	82	9109
Sun 16 Sep	55	76	49	47	49	72	114	195	330	462	470	723	644	671	719	871	736	497	429	317	261	157	113	101	8158
Mon 17 Sep	64	43	34	34	56	181	591	1133	1531	971	794	760	793	717	747	1040	1264	1498	989	514	289	234	190	181	####
Tue 18 Sep	89	93	36	27	57	202	592	1023	1216	651	544	529	514	580	751	781	1048	1457	943	505	257	215	250	196	####
Wed 19 Sep	91	69	42	42	64	202	510	964	1332	792	553	566	468	548	655	771	1050	1098	717	422	291	192	193	139	####
Thu 20 Sep	85	69	52	65	118	229	518	998	1369	711	803	693	718	700	805	960	982	1212	668	372	278	192	146	177	####

Fri 21 Sep	99	68	49	41	51	121	372	786	1031	622	435	503	556	613	716	1007	884	902	624	404	289	230	179	153	####
Sat 22 Sep	97	71	60	65	90	115	198	303	460	581	707	720	700	684	692	705	661	525	476	335	234	188	129	130	8926
Sun 23 Sep	108	85	81	88	68	77	125	212	283	494	659	723	770	829	808	698	687	623	460	386	261	189	126	87	8927
Mon 24 Sep	72	55	45	32	59	176	629	1127	1518	934	711	659	753	812	799	1061	1349	1534	965	582	298	265	230	157	####
Tue 25 Sep	66	68	51	34	67	229	651	1181	1588	987	778	774	793	783	839	1023	1279	1598	974	569	344	267	188	154	####
Wed 26 Sep	95	57	36	56	44	225	586	1103	1428	810	685	617	715	690	802	959	1187	1417	1033	558	332	238	228	179	####
Thu 27 Sep	104	72	49	39	66	201	594	1105	1577	913	725	822	701	807	852	988	1328	1589	894	548	402	274	258	175	####
Fri 28 Sep	94	69	64	72	51	175	579	1057	1421	854	774	803	929	1016	1017	1350	1366	1234	756	558	357	271	199	187	####
Sat 29 Sep	74	89	60	57	45	107	206	293	413	643	691	792	814	851	767	761	686	651	482	431	351	227	121	106	9718
Sun 30 Sep	56	55	41	54	31	75	114	184	350	521	710	812	900	746	698	613	635	502	440	324	294	206	105	82	8548
September Average	79.6	65.9	44.4	44	59.1	166	449	817	1068	736	679	683	723	733	780	906	1008	1120	739	462	311	219	175	137	####
Mon 1 Oct	41	36	26	37	65	177	606	1109	1632	1024	836	764	809	806	912	1091	1285	1624	969	423	299	200	217	165	####
Tue 2 Oct	75	50	30	33	60	178	597	1007	1602	963	695	724	729	692	783	938	1399	1878	1099	563	411	280	227	161	####
Wed 3 Oct	91	55	36	30	55	195	597	1070	1476	936	661	696	668	787	802	926	1327	1690	1016	517	370	235	213	155	####
Thu 4 Oct	100	66	29	31	63	188	561	1096	1629	965	831	755	828	888	918	1091	1465	1690	965	642	403	286	228	170	####
Fri 5 Oct	102	76	37	31	67	135	421	733	1065	581	513	542	596	661	818	848	971	954	666	458	336	267	189	154	####
Sat 6 Oct	91	66	85	124	62	129	155	226	400	543	610	650	721	782	779	727	732	671	531	420	340	213	196	115	9368
Sun 7 Oct	80	67	31	41	35	71	134	197	399	610	709	752	778	834	667	629	604	428	413	352	222	190	106	90	8439
Mon 8 Oct	59	289	176	22	53	168	536	1029	1512	921	699	717	764	743	850	1062	1487	1757	1090	594	418	320	211	165	####
Tue 9 Oct	88	41	26	24	43	190	536	939	1426	876	610	656	647	700	726	945	1316	1697	952	535	389	258	232	167	####
Wed 10 Oct	63	53	55	37	75	196	557	993	1491	981	876	861	873	912	982	1055	1399	1664	1085	563	372	314	220	178	####
Thu 11 Oct	92	68	30	45	55	184	536	894	1500	860	617	602	719	730	753	1030	1302	1592	956	530	373	273	213	150	####
Fri 12 Oct	114	58	40	29	53	148	367	585	986	635	486	491	505	616	560	902	855	785	523	398	263	204	141	111	9855
Sat 13 Oct	75	58	35	45	47	99	128	179	275	283	301	314	353	398	420	403	426	384	390	278	215	156	116	97	5475
Sun 14 Oct	86	44	44	45	48	60	101	185	298	473	473	463	455	476	399	467	460	468	434	374	229	149	114	104	6449
Mon 15 Oct	70	27	28	33	47	169	547	910	1449	929	727	776	740	763	835	850	1189	1513	947	542	357	234	202	136	####
Tue 16 Oct	63	57	31	43	70	185	579	1032	1499	906	679	702	721	723	813	1014	1398	1691	936	536	344	288	231	148	####
Wed 17 Oct	86	48	38	38	62	178	538	945	1507	857	752	748	794	875	876	1169	1463	1715	1001	521	362	262	201	144	####
Thu 18 Oct	71	54	33	32	50	164	458	883	1371	849	635	719	769	791	872	1034	1232	1544	965	550	358	280	203	160	####
Fri 19 Oct	88	68	39	45	84	137	443	735	980	748	614	693	768	831	866	898	1057	1087	658	455	299	238	195	199	####
Sat 20 Oct	95	74	66	37	43	136	154	203	352	460	481	628	657	718	703	652	601	515	411	370	274	169	119	96	8014
Sun 21 Oct	99	71	52	96	36	84	120	173	305	516	652	690	725	572	534	563	498	412	343	338	272	162	133	105	7551
Mon 22 Oct	40	21	16	24	48	131	436	777	1074	790	698	654	683	784	747	813	1036	1401	867	481	324	246	224	138	####
Tue 23 Oct	49	47	29	29	34	113	309	581	836	527	396	451	513	509	510	555	791	877	674	372	260	180	179	101	8922
Wed 24 Oct	44	34	26	28	39	138	472	777	1083	775	652	659	695	707	732	899	1021	1320	857	514	269	236	240	145	####
Thu 25 Oct	62	34	38	28	40	133	401	770	1076	777	643	692	713	735	708	876	1067	1335	805	499	337	236	223	158	####
Fri 26 Oct	91	58	39	31	57	133	394	683	930	665	636	612	653	679	784	786	909	852	605	361	282	213	165	183	####
Sat 27 Oct	66	71	23	41	56	62	99	125	221	175	182	309	437	434	448	466	380	366	387	398	285	225	76	63	5395
Sun 28 Oct	54	64	17	18	21	36	78	67	191	335	502	509	509	476	530	413	377	330	324	287	240	109	86	65	5638
Mon 29 Oct	37	41	31	15	40	101	422	690	1047	709	594	612	607	658	686	794	995	1156	710	406	311	202	185	150	####
Tue 30 Oct	56	48	27	50	73	153	436	750	1061	723	578	587	614	537	546	646	953	1126	685	465	318	295	203	197	####
Wed 31 Oct	62	58	25	33	45	127	391	807	1064	786	685	631	713	697	648	729	939	1049	641	426	266	179	132	137	####
October Average	73.9	61.4	39.9	38.5	52.5	139	391	682	1024	715	614	634	670	694	716	815	998	1147	739	457	316	229	181	139	####
Thu 1 Nov	68	73	33	57	44	114	391	641	787	592	462	463	672	629	659	707	883	964	661	403	294	257	170	127	####
Fri 2 Nov	69	80	53	37	59	135	382	668	879	710	707	747	793	821	952	853	876	857	602	378	277	211	194	182	####
Sat 3 Nov	89	104	57	170	141	117	145	236	290	351	496	561	566	517	563	406	437	371	339	268	171	140	117	112	6764
Sun 4 Nov	40	39	25	18	25	60	121	173	285	469	659	679	627	595	643	554	453	407	377	293	252	155	83	47	7079
Mon 5 Nov	36	27	23	82	43	149	403	845	1189	937	722	621	735	645	651	791	981	1199	672	412	295	243	132	148	####

Tue 6 Nov	60	48	23	38	64	151	440	835	1169	846	672	714	672	682	688	888	1045	1274	795	463	338	254	201	117	####
Wed 7 Nov	60	59	31	37	54	141	406	821	1091	721	564	524	591	567	564	719	876	1078	642	399	275	215	177	132	####
Thu 8 Nov	56	64	28	39	63	138	436	793	1175	839	714	722	771	725	737	857	1027	1214	797	486	324	207	183	130	####
Fri 9 Nov	77	46	33	37	37	113	349	678	915	710	583	627	724	689	697	762	825	839	562	410	242	143	130	96	####
Sat 10 Nov	32	28	24	23	32	87	106	184	283	424	542	670	708	649	566	533	429	410	393	306	255	172	112	81	7049
Sun 11 Nov	55	36	46	74	108	106	99	161	277	508	570	532	631	496	441	405	388	406	319	293	204	141	98	59	6453
Mon 12 Nov	42	28	21	20	41	125	447	781	1122	811	677	615	664	719	655	800	910	1157	804	414	305	193	177	114	####
Tue 13 Nov	61	62	28	32	39	143	426	849	1149	887	727	609	640	612	690	784	1016	1231	893	472	307	253	185	136	####
Wed 14 Nov	59	41	26	31	52	93	360	779	1083	693	530	512	619	596	553	692	887	1007	700	409	274	217	167	105	####
Thu 15 Nov	36	30	22	18	39	105	313	687	844	608	584	602	615	579	643	686	851	936	645	338	202	162	119	95	9759
Fri 16 Nov	29	28	30	14	33	106	272	509	706	495	379	445	531	550	555	540	675	685	453	295	225	162	107	66	7890
Sat 17 Nov	33	26	28	19	23	49	87	151	220	278	439	433	483	491	451	379	282	280	263	218	142	86	108	50	5019
Sun 18 Nov	33	23	16	26	15	40	43	104	255	294	501	498	518	505	421	362	259	214	199	211	165	111	70	43	4926
Mon 19 Nov	32	10	18	18	27	83	263	526	659	503	403	346	406	442	424	509	609	750	467	297	212	149	105	59	7317
Tue 20 Nov	25	40	8	15	26	72	223	448	577	413	326	316	306	328	309	425	582	678	458	249	165	114	75	73	6251
Wed 21 Nov	20	35	18	7	24	101	197	410	576	331	276	312	369	429	438	472	606	685	462	307	211	128	96	66	6576
Thu 22 Nov	36	29	26	21	28	85	265	488	699	378	297	268	312	285	385	475	488	696	407	289	192	172	95	61	6477
Fri 23 Nov	42	20	22	21	30	93	260	463	665	433	423	466	582	548	548	551	693	697	430	308	205	143	106	88	7837
Sat 24 Nov	58	25	26	19	40	71	105	186	269	350	444	485	469	488	520	489	375	325	308	224	165	159	101	77	5778
Sun 25 Nov	40	24	26	27	22	40	72	74	127	255	296	434	376	342	360	241	249	229	232	177	134	117	57	45	3996
Mon 26 Nov	10	17	11	5	31	88	275	494	740	492	427	418	445	458	478	489	724	825	580	329	217	150	100	70	7873
Tue 27 Nov	30	30	32	11	22	86	310	628	900	587	451	552	543	457	439	618	757	831	515	263	157	144	90	53	8506
Wed 28 Nov	21	13	12	19	36	77	232	449	700	449	357	324	351	326	351	496	545	666	451	251	174	122	101	77	6600
Thu 29 Nov	23	21	11	15	35	81	220	408	613	348	309	305	267	310	353	464	509	628	398	251	164	117	83	56	5989
Fri 30 Nov	20	18	14	9	21	93	216	451	621	456	380	451	553	502	513	661	859	769	430	241	178	130	98	44	7728
November Average	43.1	37.5	25.7	32	41.8	98.1	262	497	696	539	497	508	551	533	542	587	670	744	508	322	224	166	121	87	####
Sat 1 Dec	40	23	24	27	20	52	81	88	172	187	174	212	218	189	207	179	194	203	203	166	107	86	80	29	2961
Sun 2 Dec	25	22	18	19	26	36	48	55	111	198	269	268	290	282	311	256	225	170	171	167	118	77	52	32	3246
Mon 3 Dec	33	8	6	13	32	74	258	506	703	385	354	393	437	382	495	598	831	816	523	318	226	144	103	54	7692
Tue 4 Dec	45	25	22	23	33	103	250	412	686	360	314	296	372	404	374	645	876	1000	512	325	199	130	113	73	7592
Wed 5 Dec	27	30	22	25	33	90	211	416	702	322	198	200	204	235	234	545	798	708	394	212	152	112	105	59	6034
Thu 6 Dec	47	24	23	22	27	90	270	597	992	491	333	320	398	348	432	721	977	1247	518	350	220	177	110	92	8826
Fri 7 Dec	49	25	23	22	26	59	235	416	723	362	352	367	454	451	469	820	831	652	396	235	179	150	111	71	7478
Sat 8 Dec	40	32	48	17	28	45	95	90	138	180	242	321	302	402	314	315	283	248	272	213	122	90	68	48	3953
Sun 9 Dec	25	19	18	22	18	29	46	84	138	266	401	436	521	463	420	362	276	217	271	198	164	124	72	60	4650
Mon 10 Dec	29	23	12	11	21	63	230	468	794	460	423	342	420	364	452	587	768	954	588	346	209	155	126	75	7920
Tue 11 Dec	29	25	20	13	25	79	274	469	871	475	382	430	405	431	479	765	1010	1365	595	314	194	164	132	100	9046
Wed 12 Dec	42	56	25	21	40	113	297	584	875	511	389	407	463	426	483	567	712	926	561	295	221	120	93	83	8310
Thu 13 Dec	39	48	28	22	42	90	258	464	698	411	316	336	403	438	414	482	550	758	463	216	209	101	127	92	7005
Fri 14 Dec	47	26	21	11	31	76	235	378	582	321	304	350	400	432	457	564	458	468	302	202	145	103	90	70	6073
Sat 15 Dec	29	14	21	5	12	51	52	86	101	166	177	199	256	188	218	166	115	97	86	50	36	30	38	22	2215
Sun 16 Dec	12	4	18	7	15	19	31	32	55	153	217	250	270	279	281	201	155	139	128	89	110	49	58	25	2597
Mon 17 Dec	17	10	8	10	23	68	202	376	572	313	249	251	319	344	292	487	503	503	326	138	122	63	97	71	5364
Tue 18 Dec	32	36	16	20	32	82	222	370	452	248	170	184	225	209	210	428	385	435	275	159	96	68	110	89	4553
Wed 19 Dec	36	22	10	23	25	71	254	428	498	320	312	292	274	316	343	521	506	562	341	208	129	95	102	84	5772
Thu 20 Dec	45	39	16	20	37	67	233	373	487	347	251	307	316	354	329	435	423	464	324	203	148	98	96	79	5491
Fri 21 Dec	52	54	20	25	44	65	219	282	349	230	227	275	341	329	319	359	353	321	236	145	111	99	46	45	4546
Sat 22 Dec	23	15	18	17	18	42	52	73	132	166	255	305	294	291	367	267	175	174	154	110	94	48	57	26	3173

Sun 23 Dec	13	12	9	28	11	24	29	33	81	158	199	222	218	217	222	180	160	104	81	61	66	35	34	26	2223
Mon 24 Dec	14	6	10	7	12	20	40	85	139	181	232	271	304	282	250	253	167	128	89	58	41	30	19	14	2652
Tue 25 Dec	2	1	2	2	6	2	7	16	22	29	50	79	82	46	62	55	37	39	28	31	25	9	11	7	650
Wed 26 Dec	5	4	1	4	4	11	14	32	54	115	202	232	269	233	243	147	120	112	50	44	45	28	25	6	2000
Thu 27 Dec	10	5	3	5	8	22	51	96	127	139	171	264	379	325	323	232	173	184	90	59	37	39	37	11	2790
Fri 28 Dec	9	4	4	7	13	16	44	85	129	163	205	266	277	275	270	241	178	129	85	74	39	24	20	8	2565
Sat 29 Dec	17	10	7	11	11	24	31	46	54	80	96	142	155	169	203	187	125	111	70	66	67	32	30	14	1758
Sun 30 Dec	4	4	1	6	9	13	16	38	62	113	163	210	243	231	225	173	125	78	67	49	35	24	13	9	1911
Mon 31 Dec	9	2	13	35	40	46	50	55	97	137	230	336	298	255	267	216	156	104	89	35	30	29	11	15	2555
December Average	27.3	20.3	15.7	16.1	23.3	53	140	243	374	258	253	283	316	309	321	386	408	433	267	166	119	81.7	70.5	48	####

Appendix B: Yearly number of Lighting Hours

Hour Ending	L1	L2	L3	L4	L5	L6	L7	L8	L9	L10	L11	L12	L13	L14	L15	L16	L17	L18	L19	L20	L21	L22	L23	L24	Total
Mon 1 Jan	0	0	0	0	0	0	0	0	0.48	1	1	1	1	1	1	0.82	0	0	0	0	0	0	0	0	7.3
Tue 2 Jan	0	0	0	0	0	0	0	0	0.48	1	1	1	1	1	1	0.83	0	0	0	0	0	0	0	0	7.31
Wed 3 Jan	0	0	0	0	0	0	0	0	0.48	1	1	1	1	1	1	0.83	0	0	0	0	0	0	0	0	7.31
Thu 4 Jan	0	0	0	0	0	0	0	0	0.5	1	1	1	1	1	1	0.88	0	0	0	0	0	0	0	0	7.38
Fri 5 Jan	0	0	0	0	0	0	0	0	0.5	1	1	1	1	1	1	0.9	0	0	0	0	0	0	0	0	7.4
Sat 6 Jan	0	0	0	0	0	0	0	0	0.52	1	1	1	1	1	1	0.92	0	0	0	0	0	0	0	0	7.44
Sun 7 Jan	0	0	0	0	0	0	0	0	0.52	1	1	1	1	1	1	0.95	0	0	0	0	0	0	0	0	7.47
Mon 8 Jan	0	0	0	0	0	0	0	0	0.53	1	1	1	1	1	1	0.97	0	0	0	0	0	0	0	0	7.5
Tue 9 Jan	0	0	0	0	0	0	0	0	0.53	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	7.53
Wed 10 Jan	0	0	0	0	0	0	0	0	0.55	1	1	1	1	1	1	1	0.02	0	0	0	0	0	0	0	7.57
Thu 11 Jan	0	0	0	0	0	0	0	0	0.57	1	1	1	1	1	1	1	0.05	0	0	0	0	0	0	0	7.62
Fri 12 Jan	0	0	0	0	0	0	0	0	0.58	1	1	1	1	1	1	1	0.08	0	0	0	0	0	0	0	7.66
Sat 13 Jan	0	0	0	0	0	0	0	0	0.6	1	1	1	1	1	1	1	0.1	0	0	0	0	0	0	0	7.7
Sun 14 Jan	0	0	0	0	0	0	0	0	0.62	1	1	1	1	1	1	1	0.13	0	0	0	0	0	0	0	7.75
Mon 15 Jan	0	0	0	0	0	0	0	0	0.63	1	1	1	1	1	1	1	0.17	0	0	0	0	0	0	0	7.8
Tue 16 Jan	0	0	0	0	0	0	0	0	0.65	1	1	1	1	1	1	1	0.18	0	0	0	0	0	0	0	7.83
Wed 17 Jan	0	0	0	0	0	0	0	0	0.67	1	1	1	1	1	1	1	0.22	0	0	0	0	0	0	0	7.89
Thu 18 Jan	0	0	0	0	0	0	0	0	0.67	1	1	1	1	1	1	1	0.22	0	0	0	0	0	0	0	7.89
Fri 19 Jan	0	0	0	0	0	0	0	0	0.7	1	1	1	1	1	1	1	0.28	0	0	0	0	0	0	0	7.98
Sat 20 Jan	0	0	0	0	0	0	0	0	0.72	1	1	1	1	1	1	1	0.32	0	0	0	0	0	0	0	8.04
Sun 21 Jan	0	0	0	0	0	0	0	0	0.75	1	1	1	1	1	1	1	0.35	0	0	0	0	0	0	0	8.1
Mon 22 Jan	0	0	0	0	0	0	0	0	0.77	1	1	1	1	1	1	1	0.38	0	0	0	0	0	0	0	8.15
Tue 23 Jan	0	0	0	0	0	0	0	0	0.8	1	1	1	1	1	1	1	0.42	0	0	0	0	0	0	0	8.22
Wed 24 Jan	0	0	0	0	0	0	0	0	0.82	1	1	1	1	1	1	1	0.47	0	0	0	0	0	0	0	8.29
Thu 25 Jan	0	0	0	0	0	0	0	0	0.85	1	1	1	1	1	1	1	0.48	0	0	0	0	0	0	0	8.33
Fri 26 Jan	0	0	0	0	0	0	0	0	0.87	1	1	1	1	1	1	1	0.52	0	0	0	0	0	0	0	8.39
Sat 27 Jan	0	0	0	0	0	0	0	0	0.9	1	1	1	1	1	1	1	0.55	0	0	0	0	0	0	0	8.45
Sun 28 Jan	0	0	0	0	0	0	0	0	0.92	1	1	1	1	1	1	1	0.58	0	0	0	0	0	0	0	8.5
Mon 29 Jan	0	0	0	0	0	0	0	0	0.95	1	1	1	1	1	1	1	0.62	0	0	0	0	0	0	0	8.57
Tue 30 Jan	0	0	0	0	0	0	0	0	0.98	1	1	1	1	1	1	1	0.65	0	0	0	0	0	0	0	8.63
Wed 31 Jan	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0.68	0	0	0	0	0	0	0	8.68
Thu 1 Feb	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0.72	0	0	0	0	0	0	0	8.75
Fri 2 Feb	0	0	0	0	0	0	0	0.1	1	1	1	1	1	1	1	1	0.73	0	0	0	0	0	0	0	8.78
Sat 3 Feb	0	0	0	0	0	0	0	0.1	1	1	1	1	1	1	1	1	0.78	0	0	0	0	0	0	0	8.88
Sun 4 Feb	0	0	0	0	0	0	0	0.1	1	1	1	1	1	1	1	1	0.82	0	0	0	0	0	0	0	8.95
Mon 5 Feb	0	0	0	0	0	0	0	0.2	1	1	1	1	1	1	1	1	0.85	0	0	0	0	0	0	0	9.02
Tue 6 Feb	0	0	0	0	0	0	0	0.2	1	1	1	1	1	1	1	1	0.88	0	0	0	0	0	0	0	9.08
Wed 7 Feb	0	0	0	0	0	0	0	0.2	1	1	1	1	1	1	1	1	0.93	0	0	0	0	0	0	0	9.15
Thu 8 Feb	0	0	0	0	0	0	0	0.3	1	1	1	1	1	1	1	1	0.97	0	0	0	0	0	0	0	9.22
Fri 9 Feb	0	0	0	0	0	0	0	0.3	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	9.28
Sat 10 Feb	0	0	0	0	0	0	0	0.3	1	1	1	1	1	1	1	1	1	0.03	0	0	0	0	0	0	9.36
Sun 11 Feb	0	0	0	0	0	0	0	0.4	1	1	1	1	1	1	1	1	1	0.07	0	0	0	0	0	0	9.44
Mon 12 Feb	0	0	0	0	0	0	0	0.4	1	1	1	1	1	1	1	1	1	0.1	0	0	0	0	0	0	9.5
Tue 13 Feb	0	0	0	0	0	0	0	0.4	1	1	1	1	1	1	1	1	1	0.13	0	0	0	0	0	0	9.56

Wed 14 Feb	0	0	0	0	0	0	0	0.5	1	1	1	1	1	1	1	1	1	0.17	0	0	0	0	0	0	9.64
Thu 15 Feb	0	0	0	0	0	0	0	0.5	1	1	1	1	1	1	1	1	1	0.2	0	0	0	0	0	0	9.7
Fri 16 Feb	0	0	0	0	0	0	0	0.5	1	1	1	1	1	1	1	1	1	0.25	0	0	0	0	0	0	9.78
Sat 17 Feb	0	0	0	0	0	0	0	0.6	1	1	1	1	1	1	1	1	1	0.28	0	0	0	0	0	0	9.86
Sun 18 Feb	0	0	0	0	0	0	0	0.6	1	1	1	1	1	1	1	1	1	0.32	0	0	0	0	0	0	9.94
Mon 19 Feb	0	0	0	0	0	0	0	0.7	1	1	1	1	1	1	1	1	1	0.35	0	0	0	0	0	0	10
Tue 20 Feb	0	0	0	0	0	0	0	0.7	1	1	1	1	1	1	1	1	1	0.38	0	0	0	0	0	0	10.1
Wed 21 Feb	0	0	0	0	0	0	0	0.7	1	1	1	1	1	1	1	1	1	0.42	0	0	0	0	0	0	10.2
Thu 22 Feb	0	0	0	0	0	0	0	0.8	1	1	1	1	1	1	1	1	1	0.45	0	0	0	0	0	0	10.2
Fri 23 Feb	0	0	0	0	0	0	0	0.8	1	1	1	1	1	1	1	1	1	0.48	0	0	0	0	0	0	10.3
Sat 24 Feb	0	0	0	0	0	0	0	0.9	1	1	1	1	1	1	1	1	1	0.52	0	0	0	0	0	0	10.4
Sun 25 Feb	0	0	0	0	0	0	0	0.9	1	1	1	1	1	1	1	1	1	0.55	0	0	0	0	0	0	10.4
Mon 26 Feb	0	0	0	0	0	0	0	0.9	1	1	1	1	1	1	1	1	1	0.58	0	0	0	0	0	0	10.5
Tue 27 Feb	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	0.62	0	0	0	0	0	0	10.6
Wed 28 Feb	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	0.65	0	0	0	0	0	0	10.7
Thu 1 Mar	0	0	0	0	0	0	0.08	1	1	1	1	1	1	1	1	1	1	0.73	0	0	0	0	0	0	10.8
Fri 2 Mar	0	0	0	0	0	0	0.1	1	1	1	1	1	1	1	1	1	1	0.75	0	0	0	0	0	0	10.9
Sat 3 Mar	0	0	0	0	0	0	0.17	1	1	1	1	1	1	1	1	1	1	0.8	0	0	0	0	0	0	11
Sun 4 Mar	0	0	0	0	0	0	0.2	1	1	1	1	1	1	1	1	1	1	0.83	0	0	0	0	0	0	11
Mon 5 Mar	0	0	0	0	0	0	0.25	1	1	1	1	1	1	1	1	1	1	0.87	0	0	0	0	0	0	11.1
Tue 6 Mar	0	0	0	0	0	0	0.28	1	1	1	1	1	1	1	1	1	1	0.9	0	0	0	0	0	0	11.2
Wed 7 Mar	0	0	0	0	0	0	0.33	1	1	1	1	1	1	1	1	1	1	0.93	0	0	0	0	0	0	11.3
Thu 8 Mar	0	0	0	0	0	0	0.37	1	1	1	1	1	1	1	1	1	1	0.97	0	0	0	0	0	0	11.3
Fri 9 Mar	0	0	0	0	0	0	0.42	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	11.4
Sat 10 Mar	0	0	0	0	0	0	0.45	1	1	1	1	1	1	1	1	1	1	1	0.03	0	0	0	0	0	11.5
Sun 11 Mar	0	0	0	0	0	0	0.5	1	1	1	1	1	1	1	1	1	1	1	0.07	0	0	0	0	0	11.6
Mon 12 Mar	0	0	0	0	0	0	0.53	1	1	1	1	1	1	1	1	1	1	1	0.1	0	0	0	0	0	11.6
Tue 13 Mar	0	0	0	0	0	0	0.58	1	1	1	1	1	1	1	1	1	1	1	0.13	0	0	0	0	0	11.7
Wed 14 Mar	0	0	0	0	0	0	0.62	1	1	1	1	1	1	1	1	1	1	1	0.17	0	0	0	0	0	11.8
Thu 15 Mar	0	0	0	0	0	0	0.67	1	1	1	1	1	1	1	1	1	1	1	0.2	0	0	0	0	0	11.9
Fri 16 Mar	0	0	0	0	0	0	0.7	1	1	1	1	1	1	1	1	1	1	1	0.23	0	0	0	0	0	11.9
Sat 17 Mar	0	0	0	0	0	0	0.72	1	1	1	1	1	1	1	1	1	1	1	0.25	0	0	0	0	0	12
Sun 18 Mar	0	0	0	0	0	0	0.78	1	1	1	1	1	1	1	1	1	1	1	0.3	0	0	0	0	0	12.1
Mon 19 Mar	0	0	0	0	0	0	0.83	1	1	1	1	1	1	1	1	1	1	1	0.33	0	0	0	0	0	12.2
Tue 20 Mar	0	0	0	0	0	0	0.88	1	1	1	1	1	1	1	1	1	1	1	0.37	0	0	0	0	0	12.3
Wed 21 Mar	0	0	0	0	0	0	0.92	1	1	1	1	1	1	1	1	1	1	1	0.38	0	0	0	0	0	12.3
Thu 22 Mar	0	0	0	0	0	0	0.97	1	1	1	1	1	1	1	1	1	1	1	0.42	0	0	0	0	0	12.4
Fri 23 Mar	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0.45	0	0	0	0	0	12.5
Sat 24 Mar	0	0	0	0	0	0.05	1	1	1	1	1	1	1	1	1	1	1	1	0.48	0	0	0	0	0	12.5
Sun 25 Mar	0	0	0	0	0	0.08	1	1	1	1	1	1	1	1	1	1	1	1	0.52	0	0	0	0	0	12.6
Mon 26 Mar	0	0	0	0	0	0.13	1	1	1	1	1	1	1	1	1	1	1	1	0.55	0	0	0	0	0	12.7
Tue 27 Mar	0	0	0	0	0	0.17	1	1	1	1	1	1	1	1	1	1	1	1	0.58	0	0	0	0	0	12.8
Wed 28 Mar	0	0	0	0	0	0.22	1	1	1	1	1	1	1	1	1	1	1	1	0.62	0	0	0	0	0	12.8
Thu 29 Mar	0	0	0	0	0	0	0.27	1	1	1	1	1	1	1	1	1	1	1	1	0.65	0	0	0	0	12.9
Fri 30 Mar	0	0	0	0	0	0	0.3	1	1	1	1	1	1	1	1	1	1	1	1	0.68	0	0	0	0	13
Sat 31 Mar	0	0	0	0	0	0	0.35	1	1	1	1	1	1	1	1	1	1	1	1	0.72	0	0	0	0	13.1
Sun 1 Apr	0	0	0	0	0	0	0.38	1	1	1	1	1	1	1	1	1	1	1	1	0.75	0	0	0	0	13.1

Mon 2 Apr	0	0	0	0	0	0	0.43	1	1	1	1	1	1	1	1	1	1	1	1	0.78	0	0	0	0	13.2
Tue 3 Apr	0	0	0	0	0	0	0.47	1	1	1	1	1	1	1	1	1	1	1	1	0.82	0	0	0	0	13.3
Wed 4 Apr	0	0	0	0	0	0	0.52	1	1	1	1	1	1	1	1	1	1	1	1	0.85	0	0	0	0	13.4
Thu 5 Apr	0	0	0	0	0	0	0.55	1	1	1	1	1	1	1	1	1	1	1	1	0.88	0	0	0	0	13.4
Fri 6 Apr	0	0	0	0	0	0	0.6	1	1	1	1	1	1	1	1	1	1	1	1	0.92	0	0	0	0	13.5
Sat 7 Apr	0	0	0	0	0	0	0.63	1	1	1	1	1	1	1	1	1	1	1	1	0.95	0	0	0	0	13.6
Sun 8 Apr	0	0	0	0	0	0	0.68	1	1	1	1	1	1	1	1	1	1	1	1	0.98	0	0	0	0	13.7
Mon 9 Apr	0	0	0	0	0	0	0.72	1	1	1	1	1	1	1	1	1	1	1	1	1	0.02	0	0	0	13.7
Tue 10 Apr	0	0	0	0	0	0	0.77	1	1	1	1	1	1	1	1	1	1	1	1	1	0.05	0	0	0	13.8
Wed 11 Apr	0	0	0	0	0	0	0.8	1	1	1	1	1	1	1	1	1	1	1	1	1	0.07	0	0	0	13.9
Thu 12 Apr	0	0	0	0	0	0	0.85	1	1	1	1	1	1	1	1	1	1	1	1	1	0.1	0	0	0	14
Fri 13 Apr	0	0	0	0	0	0	0.88	1	1	1	1	1	1	1	1	1	1	1	1	1	0.13	0	0	0	14
Sat 14 Apr	0	0	0	0	0	0	0.93	1	1	1	1	1	1	1	1	1	1	1	1	1	0.17	0	0	0	14.1
Sun 15 Apr	0	0	0	0	0	0	0.97	1	1	1	1	1	1	1	1	1	1	1	1	1	0.2	0	0	0	14.2
Mon 16 Apr	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.23	0	0	0	14.2
Tue 17 Apr	0	0	0	0	0	0.05	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.27	0	0	0	14.3
Wed 18 Apr	0	0	0	0	0	0.08	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.3	0	0	0	14.4
Thu 19 Apr	0	0	0	0	0	0.13	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.33	0	0	0	14.5
Fri 20 Apr	0	0	0	0	0	0.17	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.37	0	0	0	14.5
Sat 21 Apr	0	0	0	0	0	0.2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.4	0	0	0	14.6
Sun 22 Apr	0	0	0	0	0	0.25	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.43	0	0	0	14.7
Mon 23 Apr	0	0	0	0	0	0.28	1	1	1	1	1	1	1	1	1	1	1	1	1	1	47	0	0	0	61.3
Tue 24 Apr	0	0	0	0	0	0.32	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.5	0	0	0	14.8
Wed 25 Apr	0	0	0	0	0	0.37	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.53	0	0	0	14.9
Thu 26 Apr	0	0	0	0	0	0.4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.57	0	0	0	15
Fri 27 Apr	0	0	0	0	0	0.43	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.6	0	0	0	15
Sat 28 Apr	0	0	0	0	0	0.47	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.63	0	0	0	15.1
Sun 29 Apr	0	0	0	0	0	0.5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.65	0	0	0	15.2
Mon 30 Apr	0	0	0	0	0	0.55	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.68	0	0	0	15.2
Tue 1 May	0	0	0	0	0	0.58	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.72	0	0	0	15.3
Wed 2 May	0	0	0	0	0	0.62	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.75	0	0	0	15.4
Thu 3 May	0	0	0	0	0	0.65	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.78	0	0	0	15.4
Fri 4 May	0	0	0	0	0	0.68	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.82	0	0	0	15.5
Sat 5 May	0	0	0	0	0	0.72	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.85	0	0	0	15.6
Sun 6 May	0	0	0	0	0	0.75	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.88	0	0	0	15.6
Mon 7 May	0	0	0	0	0	0.78	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.92	0	0	0	15.7
Tue 8 May	0	0	0	0	0	0.82	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.95	0	0	0	15.8
Wed 9 May	0	0	0	0	0	0.85	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.97	0	0	0	15.8
Thu 10 May	0	0	0	0	0	0.88	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	15.9
Fri 11 May	0	0	0	0	0	0.92	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.03	0	0	16
Sat 12 May	0	0	0	0	0	0.95	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.07	0	0	16
Sun 13 May	0	0	0	0	0	0.98	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.08	0	0	16.1
Mon 14 May	0	0	0	0	0.02	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.13	0	0	16.2
Tue 15 May	0	0	0	0	0.03	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.15	0	0	16.2
Wed 16 May	0	0	0	0	0.07	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.18	0	0	16.3
Thu 17 May	0	0	0	0	0.1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.22	0	0	16.3
Fri 18 May	0	0	0	0	0.12	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.23	0	0	16.4

Sat 19 May	0	0	0	0	0.15	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.27	0	0	16.4
Sun 20 May	0	0	0	0	0.17	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.3	0	0	16.5
Mon 21 May	0	0	0	0	0.2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.32	0	0	16.5
Tue 22 May	0	0	0	0	0.22	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.35	0	0	16.6
Wed 23 May	0	0	0	0	25	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.38	0	0	41.4
Thu 24 May	0	0	0	0	0.27	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.4	0	0	16.7
Fri 25 May	0	0	0	0	0.3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.43	0	0	16.7
Sat 26 May	0	0	0	0	0.32	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.45	0	0	16.8
Sun 27 May	0	0	0	0	0.33	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.48	0	0	16.8
Mon 28 May	0	0	0	0	0.35	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.5	0	0	16.9
Tue 29 May	0	0	0	0	0.38	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.53	0	0	16.9
Wed 30 May	0	0	0	0	0.4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.55	0	0	17
Thu 31 May	0	0	0	0	0.42	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.57	0	0	17
Fri 1 Jun	0	0	0	0	0.43	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.58	0	0	17
Sat 2 Jun	0	0	0	0	0.45	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.62	0	0	17.1
Sun 3 Jun	0	0	0	0	0.47	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.63	0	0	17.1
Mon 4 Jun	0	0	0	0	0.47	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.65	0	0	17.1
Tue 5 Jun	0	0	0	0	0.48	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.67	0	0	17.2
Wed 6 Jun	0	0	0	0	0.5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.67	0	0	17.2
Thu 7 Jun	0	0	0	0	0.52	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.68	0	0	17.2
Fri 8 Jun	0	0	0	0	0.5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.7	0	0	17.2
Sat 9 Jun	0	0	0	0	0.53	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.72	0	0	17.3
Sun 10 Jun	0	0	0	0	0.53	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.73	0	0	17.3
Mon 11 Jun	0	0	0	0	0.55	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.77	0	0	17.3
Tue 12 Jun	0	0	0	0	0.55	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.77	0	0	17.3
Wed 13 Jun	0	0	0	0	0.55	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.78	0	0	17.3
Thu 14 Jun	0	0	0	0	0.55	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.8	0	0	17.4
Fri 15 Jun	0	0	0	0	0.57	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.8	0	0	17.4
Sat 16 Jun	0	0	0	0	0.57	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.82	0	0	17.4
Sun 17 Jun	0	0	0	0	0.57	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.82	0	0	17.4
Mon 18 Jun	0	0	0	0	0.57	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.82	0	0	17.4
Tue 19 Jun	0	0	0	0	0.57	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.83	0	0	17.4
Wed 20 Jun	0	0	0	0	0.57	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.83	0	0	17.4
Thu 21 Jun	0	0	0	0	0.55	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.83	0	0	17.4
Fri 22 Jun	0	0	0	0	0.55	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.83	0	0	17.4
Sat 23 Jun	0	0	0	0	0.55	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.83	0	0	17.4
Sun 24 Jun	0	0	0	0	0.47	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.83	0	0	17.3
Mon 25 Jun	0	0	0	0	0.47	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.83	0	0	17.3
Tue 26 Jun	0	0	0	0	0.52	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.83	0	0	17.4
Wed 27 Jun	0	0	0	0	0.52	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.83	0	0	17.4
Thu 28 Jun	0	0	0	0	0.5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.83	0	0	17.3
Fri 29 Jun	0	0	0	0	0.5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.82	0	0	17.3
Sat 30 Jun	0	0	0	0	0.48	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.82	0	0	17.3
Sun 1 Jul	0	0	0	0	0.48	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.82	0	0	17.3
Mon 2 Jul	0	0	0	0	0.45	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.8	0	0	17.3
Tue 3 Jul	0	0	0	0	0.43	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.8	0	0	17.2
Wed 4 Jul	0	0	0	0	0.42	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.78	0	0	17.2
Thu 5 Jul	0	0	0	0	0.4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.77	0	0	17.2

Fri 6 Jul	0	0	0	0	0.38	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.77	0	0	17.2
Sat 7 Jul	0	0	0	0	0.37	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.75	0	0	17.1
Sun 8 Jul	0	0	0	0	0.35	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.73	0	0	17.1
Mon 9 Jul	0	0	0	0	0.33	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.72	0	0	17.1
Tue 10 Jul	0	0	0	0	0.32	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.7	0	0	17
Wed 11 Jul	0	0	0	0	0.3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.68	0	0	17
Thu 12 Jul	0	0	0	0	0.27	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.68	0	0	17
Fri 13 Jul	0	0	0	0	0.25	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.65	0	0	16.9
Sat 14 Jul	0	0	0	0	0.23	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.63	0	0	16.9
Sun 15 Jul	0	0	0	0	0.2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.6	0	0	16.8
Mon 16 Jul	0	0	0	0	0.18	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.58	0	0	16.8
Tue 17 Jul	0	0	0	0	0.15	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.57	0	0	16.7
Wed 18 Jul	0	0	0	0	0.13	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.53	0	0	16.7
Thu 19 Jul	0	0	0	0	0.1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.52	0	0	16.6
Fri 20 Jul	0	0	0	0	0.08	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.5	0	0	16.6
Sat 21 Jul	0	0	0	0	0.05	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.47	0	0	16.5
Sun 22 Jul	0	0	0	0	0.02	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.45	0	0	16.5
Mon 23 Jul	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.42	0	0	16.4
Tue 24 Jul	0	0	0	0	0	0.97	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.38	0	0	16.4
Wed 25 Jul	0	0	0	0	0	0.95	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.37	0	0	16.3
Thu 26 Jul	0	0	0	0	0	0.92	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.33	0	0	16.3
Fri 27 Jul	0	0	0	0	0	0.88	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.3	0	0	16.2
Sat 28 Jul	0	0	0	0	0	0.85	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.27	0	0	16.1
Sun 29 Jul	0	0	0	0	0	0.83	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.25	0	0	16.1
Mon 30 Jul	0	0	0	0	0	0.8	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.22	0	0	16
Tue 31 Jul	0	0	0	0	0	0.77	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.18	0	0	16
Wed 1 Aug	0	0	0	0	0	0.73	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.15	0	0	15.9
Thu 2 Aug	0	0	0	0	0	0.72	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.12	0	0	15.8
Fri 3 Aug	0	0	0	0	0	0.68	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.08	0	0	15.8
Sat 4 Aug	0	0	0	0	0	0.65	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.05	0	0	15.7
Sun 5 Aug	0	0	0	0	0	0.62	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.02	0	0	15.6
Mon 6 Aug	0	0	0	0	0	0.58	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.98	0	0	0	15.6
Tue 7 Aug	0	0	0	0	0	0.57	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.95	0	0	0	15.5
Wed 8 Aug	0	0	0	0	0	0.53	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.92	0	0	0	15.5
Thu 9 Aug	0	0	0	0	0	0.5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.88	0	0	0	15.4
Fri 10 Aug	0	0	0	0	0	0.47	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.83	0	0	0	15.3
Sat 11 Aug	0	0	0	0	0	0.42	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.8	0	0	0	15.2
Sun 12 Aug	0	0	0	0	0	0.4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.77	0	0	0	15.2
Mon 13 Aug	0	0	0	0	0	0.37	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.73	0	0	0	15.1
Tue 14 Aug	0	0	0	0	0	0.35	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.72	0	0	0	15.1
Wed 15 Aug	0	0	0	0	0	0.32	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.65	0	0	0	15
Thu 16 Aug	0	0	0	0	0	0.28	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.62	0	0	0	14.9
Fri 17 Aug	0	0	0	0	0	0.25	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.58	0	0	0	14.8
Sat 18 Aug	0	0	0	0	0	0.22	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.53	0	0	0	14.8
Sun 19 Aug	0	0	0	0	0	0.18	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.5	0	0	0	14.7

Mon 20 Aug	0	0	0	0	0	0.15	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.47	0	0	0	14.6
Tue 21 Aug	0	0	0	0	0	0.13	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.42	0	0	0	14.6
Wed 22 Aug	0	0	0	0	0	0.1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.38	0	0	0	14.5
Thu 23 Aug	0	0	0	0	0	0.07	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.35	0	0	0	14.4
Fri 24 Aug	0	0	0	0	0	0.03	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.3	0	0	0	14.3
Sat 25 Aug	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.27	0	0	0	14.3
Sun 26 Aug	0	0	0	0	0	0	0.97	1	1	1	1	1	1	1	1	1	1	1	1	1	0.22	0	0	0	14.2
Mon 27 Aug	0	0	0	0	0	0	0.93	1	1	1	1	1	1	1	1	1	1	1	1	1	0.18	0	0	0	14.1
Tue 28 Aug	0	0	0	0	0	0	0.88	1	1	1	1	1	1	1	1	1	1	1	1	1	0.13	0	0	0	14
Wed 29 Aug	0	0	0	0	0	0	0.88	1	1	1	1	1	1	1	1	1	1	1	1	1	0.1	0	0	0	14
Thu 30 Aug	0	0	0	0	0	0	0.85	1	1	1	1	1	1	1	1	1	1	1	1	1	0.05	0	0	0	13.9
Fri 31 Aug	0	0	0	0	0	0	0.82	1	1	1	1	1	1	1	1	1	1	1	1	1	0.02	0	0	0	13.8
Sat 1 Sep	0	0	0	0	0	0	0.78	1	1	1	1	1	1	1	1	1	1	1	1	0.97	0	0	0	0	13.8
Sun 2 Sep	0	0	0	0	0	0	0.75	1	1	1	1	1	1	1	1	1	1	1	1	0.93	0	0	0	0	13.7
Mon 3 Sep	0	0	0	0	0	0	0.72	1	1	1	1	1	1	1	1	1	1	1	1	0.88	0	0	0	0	13.6
Tue 4 Sep	0	0	0	0	0	0	0.68	1	1	1	1	1	1	1	1	1	1	1	1	0.85	0	0	0	0	13.5
Wed 5 Sep	0	0	0	0	0	0	0.65	1	1	1	1	1	1	1	1	1	1	1	1	0.8	0	0	0	0	13.5
Thu 6 Sep	0	0	0	0	0	0	0.63	1	1	1	1	1	1	1	1	1	1	1	1	0.77	0	0	0	0	13.4
Fri 7 Sep	0	0	0	0	0	0	0.6	1	1	1	1	1	1	1	1	1	1	1	1	0.72	0	0	0	0	13.3
Sat 8 Sep	0	0	0	0	0	0	0.57	1	1	1	1	1	1	1	1	1	1	1	1	0.68	0	0	0	0	13.3
Sun 9 Sep	0	0	0	0	0	0	0.53	1	1	1	1	1	1	1	1	1	1	1	1	0.63	0	0	0	0	13.2
Mon 10 Sep	0	0	0	0	0	0	0.5	1	1	1	1	1	1	1	1	1	1	1	1	0.6	0	0	0	0	13.1
Tue 11 Sep	0	0	0	0	0	0	0.47	1	1	1	1	1	1	1	1	1	1	1	1	0.55	0	0	0	0	13
Wed 12 Sep	0	0	0	0	0	0	0.43	1	1	1	1	1	1	1	1	1	1	1	1	0.52	0	0	0	0	13
Thu 13 Sep	0	0	0	0	0	0	0.42	1	1	1	1	1	1	1	1	1	1	1	1	0.47	0	0	0	0	12.9
Fri 14 Sep	0	0	0	0	0	0	0.38	1	1	1	1	1	1	1	1	1	1	1	1	0.42	0	0	0	0	12.8
Sat 15 Sep	0	0	0	0	0	0	0.35	1	1	1	1	1	1	1	1	1	1	1	1	0.38	0	0	0	0	12.7
Sun 16 Sep	0	0	0	0	0	0	0.32	1	1	1	1	1	1	1	1	1	1	1	1	0.33	0	0	0	0	12.7
Mon 17 Sep	0	0	0	0	0	0	0.28	1	1	1	1	1	1	1	1	1	1	1	1	0.3	0	0	0	0	12.6
Tue 18 Sep	0	0	0	0	0	0	0.25	1	1	1	1	1	1	1	1	1	1	1	1	0.25	0	0	0	0	12.5
Wed 19 Sep	0	0	0	0	0	0	0.22	1	1	1	1	1	1	1	1	1	1	1	1	0.22	0	0	0	0	12.4
Thu 20 Sep	0	0	0	0	0	0	0.2	1	1	1	1	1	1	1	1	1	1	1	1	0.17	0	0	0	0	12.4
Fri 21 Sep	0	0	0	0	0	0	0.17	1	1	1	1	1	1	1	1	1	1	1	1	0.12	0	0	0	0	12.3
Sat 22 Sep	0	0	0	0	0	0	0.13	1	1	1	1	1	1	1	1	1	1	1	1	0.08	0	0	0	0	12.2
Sun 23 Sep	0	0	0	0	0	0	0.1	1	1	1	1	1	1	1	1	1	1	1	1	0.03	0	0	0	0	12.1
Mon 24 Sep	0	0	0	0	0	0	0.07	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	12.1
Tue 25 Sep	0	0	0	0	0	0	0.03	1	1	1	1	1	1	1	1	1	1	1	0.95	0	0	0	0	0	12
Wed 26 Sep	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0.92	0	0	0	0	0	11.9
Thu 27 Sep	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0.87	0	0	0	0	0	11.8
Fri 28 Sep	0	0	0	0	0	0	0	0.9	1	1	1	1	1	1	1	1	1	1	0.82	0	0	0	0	0	11.8
Sat 29 Sep	0	0	0	0	0	0	0	0.9	1	1	1	1	1	1	1	1	1	1	0.78	0	0	0	0	0	11.7
Sun 30 Sep	0	0	0	0	0	0	0	0.9	1	1	1	1	1	1	1	1	1	1	0.73	0	0	0	0	0	11.6
Mon 1 Oct	0	0	0	0	0	0	0	0.9	1	1	1	1	1	1	1	1	1	1	0.7	0	0	0	0	0	11.6
Tue 2 Oct	0	0	0	0	0	0	0	0.8	1	1	1	1	1	1	1	1	1	1	0.65	0	0	0	0	0	11.5
Wed 3 Oct	0	0	0	0	0	0	0	0.8	1	1	1	1	1	1	1	1	1	1	0.62	0	0	0	0	0	11.4
Thu 4 Oct	0	0	0	0	0	0	0	0.8	1	1	1	1	1	1	1	1	1	1	0.57	0	0	0	0	0	11.3
Fri 5 Oct	0	0	0	0	0	0	0	0.7	1	1	1	1	1	1	1	1	1	1	0.53	0	0	0	0	0	11.3

Sat 6 Oct	0	0	0	0	0	0	0	0.7	1	1	1	1	1	1	1	1	1	1	0.48	0	0	0	0	0	11.2
Sun 7 Oct	0	0	0	0	0	0	0	0.7	1	1	1	1	1	1	1	1	1	1	0.45	0	0	0	0	0	11.1
Mon 8 Oct	0	0	0	0	0	0	0	0.6	1	1	1	1	1	1	1	1	1	1	0.4	0	0	0	0	0	11
Tue 9 Oct	0	0	0	0	0	0	0	0.6	1	1	1	1	1	1	1	1	1	1	0.37	0	0	0	0	0	11
Wed 10 Oct	0	0	0	0	0	0	0	0.6	1	1	1	1	1	1	1	1	1	1	0.32	0	0	0	0	0	10.9
Thu 11 Oct	0	0	0	0	0	0	0	0.5	1	1	1	1	1	1	1	1	1	1	0.28	0	0	0	0	0	10.8
Fri 12 Oct	0	0	0	0	0	0	0	0.5	1	1	1	1	1	1	1	1	1	1	0.23	0	0	0	0	0	10.7
Sat 13 Oct	0	0	0	0	0	0	0	0.5	1	1	1	1	1	1	1	1	1	1	0.2	0	0	0	0	0	10.7
Sun 14 Oct	0	0	0	0	0	0	0	0.4	1	1	1	1	1	1	1	1	1	1	0.17	0	0	0	0	0	10.6
Mon 15 Oct	0	0	0	0	0	0	0	0.4	1	1	1	1	1	1	1	1	1	1	0.12	0	0	0	0	0	10.5
Tue 16 Oct	0	0	0	0	0	0	0	0.4	1	1	1	1	1	1	1	1	1	1	0.08	0	0	0	0	0	10.5
Wed 17 Oct	0	0	0	0	0	0	0	0.3	1	1	1	1	1	1	1	1	1	1	0.03	0	0	0	0	0	10.4
Thu 18 Oct	0	0	0	0	0	0	0	0.3	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	10.3
Fri 19 Oct	0	0	0	0	0	0	0	0.3	1	1	1	1	1	1	1	1	1	0.97	0	0	0	0	0	0	10.2
Sat 20 Oct	0	0	0	0	0	0	0	0.2	1	1	1	1	1	1	1	1	1	0.92	0	0	0	0	0	0	10.2
Sun 21 Oct	0	0	0	0	0	0	0	0.2	1	1	1	1	1	1	1	1	1	0.88	0	0	0	0	0	0	10.1
Mon 22 Oct	0	0	0	0	0	0	0	0.2	1	1	1	1	1	1	1	1	1	0.85	0	0	0	0	0	0	10
Tue 23 Oct	0	0	0	0	0	0	0	0.1	1	1	1	1	1	1	1	1	1	0.8	0	0	0	0	0	0	9.93
Wed 24 Oct	0	0	0	0	0	0	0	0.1	1	1	1	1	1	1	1	1	1	0.77	0	0	0	0	0	0	9.87
Thu 25 Oct	0	0	0	0	0	0		0.1	1	1	1	1	1	1	1	1	0.73	0	0	0	0	0	0	0	8.8
Fri 26 Oct	0	0	0	0	0	0	0.03	1	1	1	1	1	1	1	1	1	0.7	0	0	0	0	0	0	0	9.73
Sat 27 Oct	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0.67	0	0	0	0	0	0	0	9.67
Sun 28 Oct	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0.62	0	0	0	0	0	0	0	9.59
Mon 29 Oct	0	0	0	0	0	0	0	0.9	1	1	1	1	1	1	1	1	0.58	0	0	0	0	0	0	0	9.51
Tue 30 Oct	0	0	0	0	0	0	0	0.9	1	1	1	1	1	1	1	1	0.55	0	0	0	0	0	0	0	9.43
Wed 31 Oct	0	0	0	0	0	0	0	0.9	1	1	1	1	1	1	1	1	0.52	0	0	0	0	0	0	0	9.37
Thu 1 Nov	0	0	0	0	0	0	0	0.8	1	1	1	1	1	1	1	1	0.48	0	0	0	0	0	0	0	9.3
Fri 2 Nov	0	0	0	0	0	0	0	0.8	1	1	1	1	1	1	1	1	0.45	0	0	0	0	0	0	0	9.23
Sat 3 Nov	0	0	0	0	0	0	0	0.8	1	1	1	1	1	1	1	1	0.42	0	0	0	0	0	0	0	9.17
Sun 4 Nov	0	0	0	0	0	0	0	0.7	1	1	1	1	1	1	1	1	0.38	0	0	0	0	0	0	0	9.1
Mon 5 Nov	0	0	0	0	0	0	0	0.7	1	1	1	1	1	1	1	1	0.35	0	0	0	0	0	0	0	9.03
Tue 6 Nov	0	0	0	0	0	0	0	0.7	1	1	1	1	1	1	1	1	0.32	0	0	0	0	0	0	0	8.97
Wed 7 Nov	0	0	0	0	0	0	0	0.6	1	1	1	1	1	1	1	1	0.28	0	0	0	0	0	0	0	8.9
Thu 8 Nov	0	0	0	0	0	0	0	0.6	1	1	1	1	1	1	1	1	0.25	0	0	0	0	0	0	0	8.83
Fri 9 Nov	0	0	0	0	0	0	0	0.6	1	1	1	1	1	1	1	1	0.22	0	0	0	0	0	0	0	8.77
Sat 10 Nov	0	0	0	0	0	0	0	0.5	1	1	1	1	1	1	1	1	0.18	0	0	0	0	0	0	0	8.7
Sun 11 Nov	0	0	0	0	0	0	0	0.5	1	1	1	1	1	1	1	1	0.17	0	0	0	0	0	0	0	8.65
Mon 12 Nov	0	0	0	0	0	0	0	0.5	1	1	1	1	1	1	1	1	0.13	0	0	0	0	0	0	0	8.58
Tue 13 Nov	0	0	0	0	0	0	0	0.4	1	1	1	1	1	1	1	1	0.1	0	0	0	0	0	0	0	8.52
Wed 14 Nov	0	0	0	0	0	0	0	0.4	1	1	1	1	1	1	1	1	0.08	0	0	0	0	0	0	0	8.46
Thu 15 Nov	0	0	0	0	0	0	0	0.4	1	1	1	1	1	1	1	1	0.05	0	0	0	0	0	0	0	8.4
Fri 16 Nov	0	0	0	0	0	0	0	0.3	1	1	1	1	1	1	1	1	0.02	0	0	0	0	0	0	0	8.34
Sat 17 Nov	0	0	0	0	0	0	0	0.3	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	8.28
Sun 18 Nov	0	0	0	0	0	0	0	0.3	1	1	1	1	1	1	1	0.97	0	0	0	0	0	0	0	0	8.22
Mon 19 Nov	0	0	0	0	0	0	0	0.2	1	1	1	1	1	1	1	0.95	0	0	0	0	0	0	0	0	8.17
Tue 20 Nov	0	0	0	0	0	0	0	0.2	1	1	1	1	1	1	1	0.93	0	0	0	0	0	0	0	0	8.11
Wed 21 Nov	0	0	0	0	0	0	0	0.2	1	1	1	1	1	1	1	0.9	0	0	0	0	0	0	0	0	8.07
Thu 22 Nov	0	0	0	0	0	0	0	0.1	1	1	1	1	1	1	1	0.9	0	0	0	0	0	0	0	0	8.03
Fri 23 Nov	0	0	0	0	0	0	0	0.1	1	1	1	1	1	1	1	0.87	0	0	0	0	0	0	0	0	7.97

Sat 24 Nov	0	0	0	0	0	0	0	0.1	1	1	1	1	1	1	1	0.83	0	0	0	0	0	0	0	0	7.9
Sun 25 Nov	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0.82	0	0	0	0	0	0	0	0	7.85
Mon 26 Nov	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0.8	0	0	0	0	0	0	0	0	7.82
Tue 27 Nov	0	0	0	0	0	0	0	0	0.98	1	1	1	1	1	1	0.78	0	0	0	0	0	0	0	0	7.76
Wed 28 Nov	0	0	0	0	0	0	0	0	0.95	1	1	1	1	1	1	0.77	0	0	0	0	0	0	0	0	7.72
Thu 29 Nov	0	0	0	0	0	0	0	0	0.93	1	1	1	1	1	1	0.75	0	0	0	0	0	0	0	0	7.68
Fri 30 Nov	0	0	0	0	0	0	0	0	0.9	1	1	1	1	1	1	0.73	0	0	0	0	0	0	0	0	7.63
Sat 1 Dec	0	0	0	0	0	0	0	0	0.85	1	1	1	1	1	1	0.73	0	0	0	0	0	0	0	0	7.58
Sun 2 Dec	0	0	0	0	0	0	0	0	0.85	1	1	1	1	1	1	0.73	0	0	0	0	0	0	0	0	7.58
Mon 3 Dec	0	0	0	0	0	0	0	0	0.82	1	1	1	1	1	1	0.7	0	0	0	0	0	0	0	0	7.52
Tue 4 Dec	0	0	0	0	0	0	0	0	0.8	1	1	1	1	1	1	0.68	0	0	0	0	0	0	0	0	7.48
Wed 5 Dec	0	0	0	0	0	0	0	0	0.77	1	1	1	1	1	1	0.68	0	0	0	0	0	0	0	0	7.45
Thu 6 Dec	0	0	0	0	0	0	0	0	0.75	1	1	1	1	1	1	0.67	0	0	0	0	0	0	0	0	7.42
Fri 7 Dec	0	0	0	0	0	0	0	0	0.75	1	1	1	1	1	1	0.67	0	0	0	0	0	0	0	0	7.42
Sat 8 Dec	0	0	0	0	0	0	0	0	0.7	1	1	1	1	1	1	0.65	0	0	0	0	0	0	0	0	7.35
Sun 9 Dec	0	0	0	0	0	0	0	0	0.68	1	1	1	1	1	1	0.65	0	0	0	0	0	0	0	0	7.33
Mon 10 Dec	0	0	0	0	0	0	0	0	0.67	1	1	1	1	1	1	0.65	0	0	0	0	0	0	0	0	7.32
Tue 11 Dec	0	0	0	0	0	0	0	0	0.65	1	1	1	1	1	1	0.65	0	0	0	0	0	0	0	0	7.3
Wed 12 Dec	0	0	0	0	0	0	0	0	0.63	1	1	1	1	1	1	0.63	0	0	0	0	0	0	0	0	7.26
Thu 13 Dec	0	0	0	0	0	0	0	0	0.62	1	1	1	1	1	1	0.63	0	0	0	0	0	0	0	0	7.25
Fri 14 Dec	0	0	0	0	0	0	0	0	0.6	1	1	1	1	1	1	0.63	0	0	0	0	0	0	0	0	7.23
Sat 15 Dec	0	0	0	0	0	0	0	0	0.58	1	1	1	1	1	1	0.63	0	0	0	0	0	0	0	0	7.21
Sun 16 Dec	0	0	0	0	0	0	0	0	0.57	1	1	1	1	1	1	0.65	0	0	0	0	0	0	0	0	7.22
Mon 17 Dec	0	0	0	0	0	0	0	0	0.55	1	1	1	1	1	1	0.65	0	0	0	0	0	0	0	0	7.2
Tue 18 Dec	0	0	0	0	0	0	0	0	0.53	1	1	1	1	1	1	0.65	0	0	0	0	0	0	0	0	7.18
Wed 19 Dec	0	0	0	0	0	0	0	0	0.53	1	1	1	1	1	1	0.65	0	0	0	0	0	0	0	0	7.18
Thu 20 Dec	0	0	0	0	0	0	0	0	0.52	1	1	1	1	1	1	0.67	0	0	0	0	0	0	0	0	7.19
Fri 21 Dec	0	0	0	0	0	0	0	0	0.52	1	1	1	1	1	1	0.67	0	0	0	0	0	0	0	0	7.19
Sat 22 Dec	0	0	0	0	0	0	0	0	0.5	1	1	1	1	1	1	0.68	0	0	0	0	0	0	0	0	7.18
Sun 23 Dec	0	0	0	0	0	0	0	0	0.5	1	1	1	1	1	1	0.7	0	0	0	0	0	0	0	0	7.2
Mon 24 Dec	0	0	0	0	0	0	0	0	0.48	1	1	1	1	1	1	0.7	0	0	0	0	0	0	0	0	7.18
Tue 25 Dec	0	0	0	0	0	0	0	0	0.48	1	1	1	1	1	1	0.72	0	0	0	0	0	0	0	0	7.2
Wed 26 Dec	0	0	0	0	0	0	0	0	0.48	1	1	1	1	1	1	0.73	0	0	0	0	0	0	0	0	7.21
Thu 27 Dec	0	0	0	0	0	0	0	0	0.48	1	1	1	1	1	1	0.75	0	0	0	0	0	0	0	0	7.23
Fri 28 Dec	0	0	0	0	0	0	0	0	0.48	1	1	1	1	1	1	0.77	0	0	0	0	0	0	0	0	7.25
Sat 29 Dec	0	0	0	0	0	0	0	0	0.48	1	1	1	1	1	1	0.78	0	0	0	0	0	0	0	0	7.26
Sun 30 Dec	0	0	0	0	0	0	0	0	0.48	1	1	1	1	1	1	0.8	0	0	0	0	0	0	0	0	7.28
Mon 31 Dec	0	0	0	0	0	0	0	0	0.48	1	1	1	1	1	1	0.82	0	0	0	0	0	0	0	0	7.3

Appendix C: Daylight Traffic flow

Hour Ending	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Total
Mon 1 Jan	0	0	0	0	0	0	0	0	29	116	140	164	217	232	209	172	0	0	0	0	0	0	0	0	1279
Tue 2 Jan	0	0	0	0	0	0	0	0	143	199	181	170	137	171	198	166	0	0	0	0	0	0	0	0	1365
Wed 3 Jan	0	0	0	0	0	0	0	0	154	171	186	229	274	269	263	202	0	0	0	0	0	0	0	0	1748
Thu 4 Jan	0	0	0	0	0	0	0	0	165	215	141	128	184	152	165	172	0	0	0	0	0	0	0	0	1322
Fri 5 Jan	0	0	0	0	0	0	0	0	174	226	228	288	368	336	403	337	0	0	0	0	0	0	0	0	2360
Sat 6 Jan	0	0	0	0	0	0	0	0	58	157	165	242	278	325	327	301	0	0	0	0	0	0	0	0	1853
Sun 7 Jan	0	0	0	0	0	0	0	0	48	173	246	318	434	320	334	276	0	0	0	0	0	0	0	0	2150
Mon 8 Jan	0	0	0	0	0	0	0	0	201	218	184	187	263	285	316	352	0	0	0	0	0	0	0	0	2006
Tue 9 Jan	0	0	0	0	0	0	0	0	292	312	220	263	223	243	287	331	0	0	0	0	0	0	0	0	2171
Wed 10 Jan	0	0	0	0	0	0	0	0	251	291	218	207	234	235	279	379	10	0	0	0	0	0	0	0	2104
Thu 11 Jan	0	0	0	0	0	0	0	0	302	329	246	290	271	300	231	326	23	0	0	0	0	0	0	0	2318
Fri 12 Jan	0	0	0	0	0	0	0	0	314	335	338	339	336	317	355	420	39	0	0	0	0	0	0	0	2793
Sat 13 Jan	0	0	0	0	0	0	0	0	73	239	253	323	327	261	241	248	24	0	0	0	0	0	0	0	1989
Sun 14 Jan	0	0	0	0	0	0	0	0	66	197	298	400	378	324	349	272	25	0	0	0	0	0	0	0	2308
Mon 15 Jan	0	0	0	0	0	0	0	0	314	291	305	334	396	394	315	418	82	0	0	0	0	0	0	0	2849
Tue 16 Jan	0	0	0	0	0	0	0	0	289	283	245	234	228	318	349	353	88	0	0	0	0	0	0	0	2387
Wed 17 Jan	0	0	0	0	0	0	0	0	206	263	234	207	196	259	261	330	76	0	0	0	0	0	0	0	2031
Thu 18 Jan	0	0	0	0	0	0	0	0	156	198	134	192	273	309	353	347	80	0	0	0	0	0	0	0	2042
Fri 19 Jan	0	0	0	0	0	0	0	0	256	310	205	262	312	316	317	400	112	0	0	0	0	0	0	0	2490
Sat 20 Jan	0	0	0	0	0	0	0	0	105	132	186	233	299	298	308	287	92	0	0	0	0	0	0	0	1940
Sun 21 Jan	0	0	0	0	0	0	0	0	55	132	142	180	176	209	185	97	30	0	0	0	0	0	0	0	1206
Mon 22 Jan	0	0	0	0	0	0	0	0	308	336	280	295	378	443	376	357	181	0	0	0	0	0	0	0	2954
Tue 23 Jan	0	0	0	0	0	0	0	0	594	492	548	526	539	446	469	540	291	0	0	0	0	0	0	0	4445
Wed 24 Jan	0	0	0	0	0	0	0	0	444	424	379	387	342	411	344	497	284	0	0	0	0	0	0	0	3513
Thu 25 Jan	0	0	0	0	0	0	0	0	545	532	437	488	441	527	528	525	337	0	0	0	0	0	0	0	4360
Fri 26 Jan	0	0	0	0	0	0	0	0	519	395	361	419	423	478	446	495	328	0	0	0	0	0	0	0	3864
Sat 27 Jan	0	0	0	0	0	0	0	0	199	243	340	375	475	431	383	347	175	0	0	0	0	0	0	0	2968
Sun 28 Jan	0	0	0	0	0	0	0	0	108	180	267	272	327	285	298	319	150	0	0	0	0	0	0	0	2206
Mon 29 Jan	0	0	0	0	0	0	0	0	702	488	390	391	456	486	472	523	462	0	0	0	0	0	0	0	4370
Tue 30 Jan	0	0	0	0	0	0	0	0	793	535	517	470	487	556	489	680	580	0	0	0	0	0	0	0	5107
Wed 31 Jan	0	0	0	0	0	0	0	0	825	521	327	384	448	543	429	557	509	0	0	0	0	0	0	0	4543
Thu 1 Feb	0	0	0	0	0	0	0	18	849	560	439	399	473	432	572	597	554	0	0	0	0	0	0	0	4893
Fri 2 Feb	0	0	0	0	0	0	0	37	949	593	493	552	558	667	705	795	674	0	0	0	0	0	0	0	6023
Sat 3 Feb	0	0	0	0	0	0	0	11	233	307	270	324	379	362	271	345	250	0	0	0	0	0	0	0	2752
Sun 4 Feb	0	0	0	0	0	0	0	12	186	371	517	583	550	540	499	429	349	0	0	0	0	0	0	0	4035
Mon 5 Feb	0	0	0	0	0	0	0	90	769	510	409	422	416	409	459	522	705	0	0	0	0	0	0	0	4711
Tue 6 Feb	0	0	0	0	0	0	0	95	644	346	223	238	251	258	323	410	530	0	0	0	0	0	0	0	3318
Wed 7 Feb	0	0	0	0	0	0	0	99	639	457	315	340	421	460	494	462	591	0	0	0	0	0	0	0	4278
Thu 8 Feb	0	0	0	0	0	0	0	127	645	412	380	391	378	412	499	443	640	0	0	0	0	0	0	0	4327
Fri 9 Feb	0	0	0	0	0	0	0	162	612	367	329	363	411	435	563	623	681	0	0	0	0	0	0	0	4546
Sat 10 Feb	0	0	0	0	0	0	0	50	184	232	286	355	373	393	426	455	351	7	0	0	0	0	0	0	3113
Sun 11 Feb	0	0	0	0	0	0	0	35	152	317	469	477	507	467	383	347	302	19	0	0	0	0	0	0	3475
Mon 12 Feb	0	0	0	0	0	0	0	184	575	441	426	505	511	500	640	651	751	84	0	0	0	0	0	0	5269
Tue 13 Feb	0	0	0	0	0	0	0	224	534	386	295	289	348	354	359	467	636	93	0	0	0	0	0	0	3985
Wed 14 Feb	0	0	0	0	0	0	0	229	536	439	346	398	394	364	360	457	503	112	0	0	0	0	0	0	4138

Thu 15 Feb	0	0	0	0	0	0	0	263	557	500	488	479	506	492	537	586	709	162	0	0	0	0	0	0	5278
Fri 16 Feb	0	0	0	0	0	0	0	299	583	511	564	597	713	687	719	689	762	185	0	0	0	0	0	0	6309
Sat 17 Feb	0	0	0	0	0	0	0	103	237	396	419	500	642	639	712	632	505	104	0	0	0	0	0	0	4889
Sun 18 Feb	0	0	0	0	0	0	0	87	303	511	662	731	700	650	617	535	407	117	0	0	0	0	0	0	5320
Mon 19 Feb	0	0	0	0	0	0	0	387	818	510	368	305	397	382	460	520	704	310	0	0	0	0	0	0	5161
Tue 20 Feb	0	0	0	0	0	0	0	484	884	588	585	496	506	520	552	814	858	391	0	0	0	0	0	0	6678
Wed 21 Feb	0	0	0	0	0	0	0	531	931	664	540	517	640	651	710	766	961	425	0	0	0	0	0	0	7336
Thu 22 Feb	0	0	0	0	0	0	0	521	794	558	561	531	554	542	598	642	897	431	0	0	0	0	0	0	6628
Fri 23 Feb	0	0	0	0	0	0	0	506	757	521	448	560	531	550	612	675	678	356	0	0	0	0	0	0	6194
Sat 24 Feb	0	0	0	0	0	0	0	183	315	367	463	532	620	561	565	481	440	170	0	0	0	0	0	0	4696
Sun 25 Feb	0	0	0	0	0	0	0	104	245	466	656	575	567	642	563	511	377	195	0	0	0	0	0	0	4901
Mon 26 Feb	0	0	0	0	0	0	0	542	749	521	379	449	430	478	479	535	684	477	0	0	0	0	0	0	5723
Tue 27 Feb	0	0	0	0	0	0	0	281	318	276	214	225	250	284	287	361	435	291	0	0	0	0	0	0	3223
Wed 28 Feb	0	0	0	0	0	0	0	166	217	161	146	200	164	253	157	218	248	103	0	0	0	0	0	0	2033
Thu 1 Mar	0	0	0	0	0	0	11	250	236	215	172	158	147	146	167	182	187	123	0	0	0	0	0	0	1994
Fri 2 Mar	0	0	0	0	0	0	10	157	158	174	137	163	195	182	167	175	194	120	0	0	0	0	0	0	1832
Sat 3 Mar	0	0	0	0	0	0	12	88	90	103	122	147	133	112	119	119	115	110	0	0	0	0	0	0	1270
Sun 4 Mar	0	0	0	0	0	0	4	24	43	55	90	91	73	85	80	85	105	103	0	0	0	0	0	0	838
Mon 5 Mar	0	0	0	0	0	0	45	388	576	416	277	369	351	339	430	503	632	750	0	0	0	0	0	0	5075
Tue 6 Mar	0	0	0	0	0	0	57	449	554	348	245	267	321	364	385	497	620	664	0	0	0	0	0	0	4771
Wed 7 Mar	0	0	0	0	0	0	131	757	818	567	525	522	550	557	596	641	919	1003	0	0	0	0	0	0	7586
Thu 8 Mar	0	0	0	0	0	0	146	731	755	567	460	488	536	538	502	638	932	954	0	0	0	0	0	0	7246
Fri 9 Mar	0	0	0	0	0	0	185	721	900	585	524	640	682	628	753	870	864	887	0	0	0	0	0	0	8239
Sat 10 Mar	0	0	0	0	0	0	64	159	192	202	259	280	282	378	351	397	318	308	8	0	0	0	0	0	3198
Sun 11 Mar	0	0	0	0	0	0	50	156	369	528	699	734	684	593	622	605	477	473	23	0	0	0	0	0	6013
Mon 12 Mar	0	0	0	0	0	0	234	795	1041	632	466	384	453	399	462	647	905	1035	60	0	0	0	0	0	7513
Tue 13 Mar	0	0	0	0	0	0	320	899	1082	721	629	608	656	650	724	877	1015	1215	104	0	0	0	0	0	9499
Wed 14 Mar	0	0	0	0	0	0	361	969	1261	749	706	622	728	661	669	928	1068	1232	132	0	0	0	0	0	####
Thu 15 Mar	0	0	0	0	0	0	331	787	979	661	411	453	436	394	400	584	765	790	105	0	0	0	0	0	7096
Fri 16 Mar	0	0	0	0	0	0	204	460	580	386	328	343	372	407	421	449	516	522	89	0	0	0	0	0	5076
Sat 17 Mar	0	0	0	0	0	0	92	116	170	193	220	247	300	277	280	249	235	225	42	0	0	0	0	0	2646
Sun 18 Mar	0	0	0	0	0	0	41	46	61	98	140	127	144	126	146	161	146	127	39	0	0	0	0	0	1402
Mon 19 Mar	0	0	0	0	0	0	292	724	788	501	397	415	382	437	509	527	699	682	153	0	0	0	0	0	6507
Tue 20 Mar	0	0	0	0	0	0	397	744	976	596	563	582	591	648	653	776	976	1164	258	0	0	0	0	0	8924
Wed 21 Mar	0	0	0	0	0	0	487	811	1052	646	545	558	571	531	542	642	899	1095	237	0	0	0	0	0	8615
Thu 22 Mar	0	0	0	0	0	0	458	825	910	651	611	594	611	676	698	782	996	1165	299	0	0	0	0	0	9276
Fri 23 Mar	0	0	0	0	0	0	430	718	1012	649	552	552	542	545	725	830	925	981	283	0	0	0	0	0	8744
Sat 24 Mar	0	0	0	0	0	7	210	314	394	598	732	740	790	870	756	716	629	586	195	0	0	0	0	0	7537
Sun 25 Mar	0	0	0	0	0	4	94	162	335	584	879	945	929	936	978	828	712	597	206	0	0	0	0	0	8189
Mon 26 Mar	0	0	0	0	0	24	515	834	1105	874	641	680	753	742	870	892	1066	1406	543	0	0	0	0	0	####
Tue 27 Mar	0	0	0	0	0	28	398	713	1078	554	462	407	423	451	513	704	852	998	414	0	0	0	0	0	7994
Wed 28 Mar	0	0	0	0	0	74	570	918	1213	757	579	744	590	630	583	788	926	1232	555	0	0	0	0	0	####
Thu 29 Mar	0	0	0	0	0	0	116	787	1003	712	775	813	771	796	903	966	1082	1163	767	400	0	0	0	0	####
Fri 30 Mar	0	0	0	0	0	0	32	151	213	287	380	434	383	485	456	401	405	406	350	152	0	0	0	0	4535
Sat 31 Mar	0	0	0	0	0	0	32	147	202	228	206	225	258	259	223	286	247	226	228	96	0	0	0	0	2863
Sun 1 Apr	0	0	0	0	0	0	20	93	235	427	561	619	671	501	467	470	392	354	305	137	0	0	0	0	5252
Mon 2 Apr	0	0	0	0	0	0	34	99	128	124	123	127	168	144	167	191	143	173	199	149	0	0	0	0	1969
Tue 3 Apr	0	0	0	0	0	0	178	634	729	529	431	437	433	446	486	536	748	961	616	329	0	0	0	0	7493

Wed 4 Apr	0	0	0	0	0	0	222	692	658	396	373	353	382	482	693	539	710	829	419	231	0	0	0	0	6979
Thu 5 Apr	0	0	0	0	0	0	82	291	316	295	307	477	400	441	373	380	489	595	411	234	0	0	0	0	5091
Fri 6 Apr	0	0	0	0	0	0	113	375	331	288	295	298	362	355	342	376	362	425	250	169	0	0	0	0	4342
Sat 7 Apr	0	0	0	0	0	0	47	135	241	246	293	302	283	216	169	129	133	110	104	67	0	0	0	0	2475
Sun 8 Apr	0	0	0	0	0	0	47	101	235	359	421	477	469	501	492	453	342	311	240	178	0	0	0	0	4626
Mon 9 Apr	0	0	0	0	0	0	163	424	404	352	385	430	425	402	403	456	565	702	446	293	3	0	0	0	5854
Tue 10 Apr	0	0	0	0	0	0	90	227	189	135	109	80	101	104	125	141	207	211	166	93	4	0	0	0	1982
Wed 11 Apr	0	0	0	0	0	0	129	238	243	197	169	184	230	193	229	230	351	358	227	149	6	0	0	0	3132
Thu 12 Apr	0	0	0	0	0	0	148	289	268	188	235	169	187	190	165	190	250	259	179	124	6	0	0	0	2847
Fri 13 Apr	0	0	0	0	0	0	106	191	195	140	150	149	233	236	209	231	257	222	188	130	10	0	0	0	2648
Sat 14 Apr	0	0	0	0	0	0	78	150	224	258	349	379	372	305	344	328	267	208	203	145	14	0	0	0	3624
Sun 15 Apr	0	0	0	0	0	0	40	119	270	401	569	491	427	415	391	345	329	228	136	97	16	0	0	0	4274
Mon 16 Apr	0	0	0	0	0	0	211	395	427	325	335	297	301	343	331	359	478	562	375	230	26	0	0	0	4995
Tue 17 Apr	0	0	0	0	0	5	227	408	485	298	285	291	237	244	282	317	461	456	378	243	37	0	0	0	4654
Wed 18 Apr	0	0	0	0	0	8	233	475	550	341	332	316	321	350	350	416	550	663	464	320	59	0	0	0	5748
Thu 19 Apr	0	0	0	0	0	9	212	434	494	333	369	396	340	401	422	426	543	596	444	307	66	0	0	0	5792
Fri 20 Apr	0	0	0	0	0	34	622	1080	1401	906	765	767	917	963	1067	1184	1400	1323	923	689	178	0	0	0	####
Sat 21 Apr	0	0	0	0	0	29	234	430	627	754	911	1039	1054	1050	1029	902	813	743	577	462	152	0	0	0	####
Sun 22 Apr	0	0	0	0	0	18	153	328	541	840	842	719	619	517	803	696	684	603	540	474	151	0	0	0	8527
Mon 23 Apr	0	0	0	0	0	60	643	1101	1551	962	687	620	699	823	803	981	1323	1703	1084	643	####	0	0	0	####
Tue 24 Apr	0	0	0	0	0	68	651	1181	1537	934	796	657	808	772	734	913	1250	1477	942	535	164	0	0	0	####
Wed 25 Apr	0	0	0	0	0	78	586	1100	1442	921	679	777	744	824	817	964	1366	1563	1120	768	262	0	0	0	####
Thu 26 Apr	0	0	0	0	0	72	589	1028	1329	841	609	562	646	683	648	939	1301	1430	982	718	254	0	0	0	####
Fri 27 Apr	0	0	0	0	0	80	547	1020	1325	992	842	801	792	866	1018	1018	1192	1342	910	605	300	0	0	0	####
Sat 28 Apr	0	0	0	0	0	48	203	329	526	564	713	821	816	749	740	613	526	550	505	458	161	0	0	0	8322
Sun 29 Apr	0	0	0	0	0	31	146	256	468	702	841	925	862	825	787	808	787	725	661	488	260	0	0	0	9572
Mon 30 Apr	0	0	0	0	0	102	529	1134	1368	811	610	606	678	680	648	906	1209	1598	1093	666	298	0	0	0	####
Tue 1 May	0	0	0	0	0	128	681	1259	1529	1019	851	834	699	784	826	987	1458	1759	1173	764	338	0	0	0	####
Wed 2 May	0	0	0	0	0	104	502	1002	1309	820	553	566	598	627	714	925	1175	1457	986	721	316	0	0	0	####
Thu 3 May	0	0	0	0	0	105	595	1084	1277	943	831	621	740	683	728	879	1389	1401	1015	612	320	0	0	0	####
Fri 4 May	0	0	0	0	0	114	564	921	1097	791	650	710	742	876	1019	1011	1172	1206	841	651	371	0	0	0	####
Sat 5 May	0	0	0	0	0	82	274	359	607	711	1009	980	983	983	981	938	708	712	596	488	286	0	0	0	####
Sun 6 May	0	0	0	0	0	47	158	301	629	824	977	960	931	986	951	803	847	710	661	497	323	0	0	0	####
Mon 7 May	0	0	0	0	0	64	176	384	622	918	992	1141	1235	1264	1129	1042	1000	866	758	618	428	0	0	0	####
Tue 8 May	0	0	0	0	0	154	718	1236	1509	1011	847	835	877	938	951	1086	1444	1620	949	619	383	0	0	0	####
Wed 9 May	0	0	0	0	0	224	751	1246	1381	928	693	710	684	697	868	1031	1372	1638	989	573	381	0	0	0	####
Thu 10 May	0	0	0	0	0	172	560	1100	1368	826	690	686	704	693	789	1025	1332	1567	1207	804	562	0	0	0	####
Fri 11 May	0	0	0	0	0	178	622	1129	1281	893	723	759	838	807	852	1056	1180	1304	766	661	442	10	0	0	####
Sat 12 May	0	0	0	0	0	127	233	345	578	766	898	969	1054	984	1080	1003	880	736	586	456	339	16	0	0	####
Sun 13 May	0	0	0	0	0	57	93	158	287	541	626	645	721	875	862	745	746	793	782	535	464	22	0	0	8952
Mon 14 May	0	0	0	0	1	185	707	1205	1500	1034	847	890	804	937	954	1244	1527	1938	1375	960	599	51	0	0	####
Tue 15 May	0	0	0	0	2	234	784	1371	1621	1071	846	793	856	940	909	1165	1623	1969	1376	975	616	59	0	0	####
Wed 16 May	0	0	0	0	5	193	664	1162	1480	791	595	606	664	631	717	1015	1327	1661	1188	762	544	66	0	0	####
Thu 17 May	0	0	0	0	4	95	323	493	510	354	325	305	316	355	430	439	580	643	466	348	236	33	0	0	6256
Fri 18 May	0	0	0	0	4	94	310	459	527	397	344	416	425	401	452	567	483	525	383	295	168	34	0	0	6284
Sat 19 May	0	0	0	0	4	91	127	199	324	441	457	557	568	503	539	491	404	327	262	217	176	34	0	0	5721
Sun 20 May	0	0	0	0	2	47	97	209	339	498	574	560	522	523	623	534	449	436	346	243	188	35	0	0	6225
Mon 21 May	0	0	0	0	7	102	309	466	513	369	380	363	393	451	403	501	647	721	584	348	240	53	0	0	6851

Tue 22 May	0	0	0	0	7	88	253	372	370	236	203	190	269	268	255	326	435	498	422	259	174	37	0	0	4663
Wed 23 May	0	0	0	0	700	106	285	420	492	303	336	324	262	285	332	400	491	548	460	285	183	53	0	0	6265
Thu 24 May	0	0	0	0	8	87	290	406	455	323	316	309	280	327	382	448	490	536	405	274	187	46	0	0	5569
Fri 25 May	0	0	0	0	9	91	242	386	380	325	274	319	298	335	340	367	320	288	201	144	128	38	0	0	4485
Sat 26 May	0	0	0	0	8	72	98	153	233	305	338	378	369	406	378	369	334	272	250	205	115	36	0	0	4320
Sun 27 May	0	0	0	0	4	47	76	153	264	446	497	507	448	472	478	438	447	342	303	215	137	59	0	0	5333
Mon 28 May	0	0	0	0	8	57	73	132	230	319	422	471	497	518	601	546	483	371	277	218	157	63	0	0	5443
Tue 29 May	0	0	0	0	8	81	198	343	320	293	250	262	286	300	319	347	422	540	367	243	181	58	0	0	4818
Wed 30 May	0	0	0	0	11	60	212	328	356	263	238	266	279	264	277	336	449	494	344	235	163	52	0	0	4627
Thu 31 May	0	0	0	0	13	61	197	329	363	280	337	296	339	380	392	389	496	610	490	334	234	83	0	0	5623
Fri 1 Jun	0	0	0	0	34	198	590	1033	1132	839	866	865	935	1035	1137	1122	1240	1287	1010	743	542	242	0	0	####
Sat 2 Jun	0	0	0	0	27	168	230	390	601	701	775	768	881	870	846	771	719	614	444	351	246	131	0	0	9533
Sun 3 Jun	0	0	0	0	46	105	190	224	439	572	786	762	824	745	728	835	712	740	559	420	424	153	0	0	9264
Mon 4 Jun	0	0	0	0	29	192	615	993	1238	750	687	683	696	752	871	1047	1329	1553	1077	688	433	218	0	0	####
Tue 5 Jun	0	0	0	0	33	261	699	1265	1556	832	823	767	794	968	961	1133	1577	1899	1398	889	540	284	0	0	####
Wed 6 Jun	0	0	0	0	38	263	725	1139	1407	948	704	616	795	737	864	1081	1308	1700	1281	876	505	253	0	0	####
Thu 7 Jun	0	0	0	0	40	252	711	1310	1432	934	730	756	826	893	933	1159	1404	1720	1209	776	526	271	0	0	####
Fri 8 Jun	0	0	0	0	38	244	669	1141	1281	829	746	776	832	846	937	1127	1199	1336	904	630	406	224	0	0	####
Sat 9 Jun	0	0	0	0	39	192	247	415	709	738	775	827	902	879	939	830	985	801	652	429	331	207	0	0	####
Sun 10 Jun	0	0	0	0	25	183	178	372	575	822	969	1135	1274	1099	1066	1027	791	609	528	373	385	199	0	0	####
Mon 11 Jun	0	0	0	0	69	302	693	1325	1568	866	777	771	783	825	883	991	1516	1795	1079	689	479	213	0	0	####
Tue 12 Jun	0	0	0	0	69	254	785	1429	1520	988	793	765	792	857	968	1066	1412	1860	1268	731	499	290	0	0	####
Wed 13 Jun	0	0	0	0	91	312	765	1310	1498	959	765	794	849	815	880	1163	1407	1700	1107	623	412	264	0	0	####
Thu 14 Jun	0	0	0	0	36	169	497	843	881	565	427	434	400	477	542	743	918	896	711	507	414	250	0	0	9711
Fri 15 Jun	0	0	0	0	48	200	634	1122	1183	882	792	742	776	883	1026	1015	1198	1206	845	481	361	262	0	0	####
Sat 16 Jun	0	0	0	0	27	103	255	368	443	538	636	677	693	744	645	680	494	488	483	419	324	153	0	0	8171
Sun 17 Jun	0	0	0	0	21	92	203	294	622	804	1098	1320	1235	1131	1038	907	749	578	483	362	274	148	0	0	####
Mon 18 Jun	0	0	0	0	36	220	700	1162	1403	946	782	677	716	758	819	1117	1463	1727	919	509	344	310	0	0	####
Tue 19 Jun	0	0	0	0	98	246	811	1381	1560	911	762	705	807	806	877	1125	1345	1902	1236	700	391	259	0	0	####
Wed 20 Jun	0	0	0	0	39	224	582	1167	1268	798	569	595	544	620	679	932	1246	1522	1024	653	387	236	0	0	####
Thu 21 Jun	0	0	0	0	84	302	921	1360	1559	1048	829	798	820	918	847	1179	1367	1738	1210	791	514	314	0	0	####
Fri 22 Jun	0	0	0	0	37	215	705	1302	1481	1038	957	959	1020	1080	1157	1312	1522	1465	1050	691	522	300	0	0	####
Sat 23 Jun	0	0	0	0	35	182	304	414	645	731	820	896	1038	960	1088	864	833	684	605	477	326	200	0	0	####
Sun 24 Jun	0	0	0	0	23	113	200	358	711	935	1090	1151	1099	931	848	886	1000	823	692	542	478	264	0	0	####
Mon 25 Jun	0	0	0	0	50	231	763	1289	1585	1079	922	848	935	911	984	1178	1538	1932	1294	887	536	342	0	0	####
Tue 26 Jun	0	0	0	0	42	255	786	1463	1524	1001	821	861	945	921	1029	1167	1686	2095	1386	939	527	283	0	0	####
Wed 27 Jun	0	0	0	0	37	264	826	1349	1552	944	890	877	950	898	1017	1280	1505	1857	1434	909	578	422	0	0	####
Thu 28 Jun	0	0	0	0	55	234	753	1338	1609	985	938	941	931	1001	1003	1240	1474	1706	1149	696	406	334	0	0	####
Fri 29 Jun	0	0	0	0	41	225	668	1123	1332	941	891	829	807	1055	1041	1524	1295	1300	840	541	439	290	0	0	####
Sat 30 Jun	0	0	0	0	29	146	232	337	555	719	771	992	1011	1025	974	869	853	725	583	425	366	210	0	0	####
p **Sun 1 Jul**	0	0	0	0	21	85	202	350	606	789	920	1216	1087	1194	1061	1011	896	730	611	469	326	203	0	0	####
Mon 2 Jul	0	0	0	0	32	211	687	1261	1599	950	774	803	815	853	851	1049	1421	1843	1237	764	482	287	0	0	####
Tue 3 Jul	0	0	0	0	60	264	830	1275	1530	869	843	835	877	842	916	1127	1572	1898	1122	600	336	254	0	0	####
Wed 4 Jul	0	0	0	0	32	199	728	1296	1500	851	728	684	753	750	893	1198	1493	1939	1237	834	526	289	0	0	####
Thu 5 Jul	0	0	0	0	22	217	766	1330	1535	959	828	862	764	835	824	1245	1386	1779	1266	754	495	269	0	0	####
Fri 6 Jul	0	0	0	0	26	189	627	1249	1376	875	839	863	826	1007	1169	1331	1275	1458	916	684	491	259	0	0	####
Sat 7 Jul	0	0	0	0	31	185	336	431	681	825	886	910	866	831	761	529	418	636	601	501	360	224	0	0	####
Sun 8 Jul	0	0	0	0	14	112	179	372	573	955	962	961	905	912	884	779	739	680	636	454	354	158	0	0	####

Mon 9 Jul	0	0	0	0	17	231	622	1165	1465	848	663	670	581	671	750	902	1387	1718	1151	694	485	230	0	0	####
Tue 10 Jul	0	0	0	0	20	274	747	1360	1603	942	694	784	787	886	820	1231	1609	2174	1468	774	521	261	0	0	####
Wed 11 Jul	0	0	0	0	18	239	748	1303	1429	1001	713	856	831	903	926	1209	1547	1721	1084	508	267	199	0	0	####
Thu 12 Jul	0	0	0	0	16	197	636	1074	1406	869	739	780	767	782	902	1045	1296	1618	1225	757	531	250	0	0	####
Fri 13 Jul	0	0	0	0	14	242	607	1157	1301	893	718	826	843	890	1038	1295	1259	1316	908	628	476	241	0	0	####
Sat 14 Jul	0	0	0	0	11	153	235	429	729	722	873	981	1037	1062	970	799	785	719	671	554	408	195	0	0	####
Sun 15 Jul	0	0	0	0	4	80	158	314	615	754	937	1023	1071	1022	960	875	769	621	661	557	449	148	0	0	####
Mon 16 Jul	0	0	0	0	8	206	659	1092	1348	887	674	696	591	533	540	778	1135	1331	947	547	420	153	0	0	####
Tue 17 Jul	0	0	0	0	6	178	617	1180	1554	944	800	711	668	675	782	1010	1258	1639	1168	773	506	196	0	0	####
Wed 18 Jul	0	0	0	0	7	243	764	1257	1577	1046	829	876	911	854	849	1166	1700	1851	1219	726	532	175	0	0	####
Thu 19 Jul	0	0	0	0	7	226	751	1297	1633	944	891	875	887	878	981	1265	1538	1914	1254	860	615	193	0	0	####
Fri 20 Jul	0	0	0	0	10	273	634	1142	1303	929	714	765	765	791	798	752	1016	1129	706	435	357	139	0	0	####
Sat 21 Jul	0	0	0	0	3	131	263	377	539	716	828	909	898	841	830	885	756	726	599	473	336	125	0	0	####
Sun 22 Jul	0	0	0	0	1	92	209	359	598	760	1113	995	1061	983	1065	928	829	820	692	498	370	118	0	0	####
Mon 23 Jul	0	0	0	0	0	178	582	1012	1297	881	764	844	880	858	870	977	1350	1721	1125	708	418	124	0	0	####
Tue 24 Jul	0	0	0	0	0	181	705	1101	1255	884	802	779	781	829	821	903	1369	1732	1137	780	520	128	0	0	####
Wed 25 Jul	0	0	0	0	0	179	589	1125	1496	954	946	940	965	950	1052	1106	1563	1949	1377	902	686	156	0	0	####
Thu 26 Jul	0	0	0	0	0	180	553	1107	1354	980	848	891	931	900	1023	1159	1433	1736	1183	730	571	117	0	0	####
Fri 27 Jul	0	0	0	0	0	142	481	942	1094	817	662	611	640	768	829	850	1003	1091	760	556	383	60	0	0	####
Sat 28 Jul	0	0	0	0	0	100	176	260	433	506	492	497	614	626	688	686	588	484	371	266	252	48	0	0	7087
Sun 29 Jul	0	0	0	0	0	48	122	191	263	275	468	608	483	480	452	433	352	368	415	389	312	47	0	0	5706
Mon 30 Jul	0	0	0	0	0	149	491	997	1196	925	766	821	901	873	758	992	1431	1666	820	480	359	56	0	0	####
Tue 31 Jul	0	0	0	0	0	159	587	1100	1327	947	783	814	860	815	832	1010	1338	1780	1129	696	486	56	0	0	####
Wed 1 Aug	0	0	0	0	0	134	599	1032	1196	907	762	841	824	895	906	979	1267	1455	795	470	353	39	0	0	####
Thu 2 Aug	0	0	0	0	0	137	512	1026	1202	890	768	873	898	884	910	980	1347	1609	1224	829	498	41	0	0	####
Fri 3 Aug	0	0	0	0	0	105	480	917	977	598	500	432	524	550	512	695	995	1064	699	416	360	19	0	0	9844
Sat 4 Aug	0	0	0	0	0	90	219	373	562	731	773	918	887	859	866	925	772	683	550	420	337	12	0	0	9977
Sun 5 Aug	0	0	0	0	0	81	180	338	559	785	945	993	1057	965	926	1000	801	707	581	483	383	4	0	0	####
Mon 6 Aug	0	0	0	0	0	125	557	925	1042	763	679	771	799	800	847	992	1350	1557	1105	745	512	0	0	0	####
Tue 7 Aug	0	0	0	0	0	116	686	1232	1389	888	890	906	896	945	1011	1097	1614	1846	1182	784	519	0	0	0	####
Wed 8 Aug	0	0	0	0	0	111	619	1114	1288	865	794	798	829	827	894	949	1268	1609	1103	776	460	0	0	0	####
Thu 9 Aug	0	0	0	0	0	113	636	1031	1192	938	823	770	817	906	952	1013	1308	1539	1077	746	443	0	0	0	####
Fri 10 Aug	0	0	0	0	0	85	563	924	1025	782	520	660	740	847	896	979	1026	1094	840	469	268	0	0	0	####
Sat 11 Aug	0	0	0	0	0	56	251	360	569	668	822	927	839	831	813	861	728	682	495	420	205	0	0	0	9527
Sun 12 Aug	0	0	0	0	0	17	143	100	150	198	257	336	469	528	632	604	572	440	390	316	176	0	0	0	5328
Mon 13 Aug	0	0	0	0	0	56	346	639	822	521	457	506	553	607	650	777	887	1201	844	568	262	0	0	0	9696
Tue 14 Aug	0	0	0	0	0	77	660	1041	1279	866	715	766	835	804	791	919	1259	1605	1059	633	321	0	0	0	####
Wed 15 Aug	0	0	0	0	0	66	641	1069	1216	819	795	720	719	719	870	1038	1142	1422	820	514	194	0	0	0	####
Thu 16 Aug	0	0	0	0	0	53	581	918	1114	753	680	823	762	706	825	981	1157	1556	818	637	259	0	0	0	####
Fri 17 Aug	0	0	0	0	0	66	614	907	1030	733	721	873	875	941	944	987	1093	1064	663	422	215	0	0	0	####
Sat 18 Aug	0	0	0	0	0	31	198	325	430	570	728	739	734	678	751	742	580	589	512	338	155	0	0	0	8100
Sun 19 Aug	0	0	0	0	0	12	94	186	304	411	573	632	642	598	670	781	683	554	440	329	149	0	0	0	7058
Mon 20 Aug	0	0	0	0	0	42	667	1020	1237	849	784	839	848	900	951	1029	1314	1378	956	509	156	0	0	0	####
Tue 21 Aug	0	0	0	0	0	28	707	1023	1211	821	613	721	774	800	895	1002	1260	1527	1062	757	223	0	0	0	####

Wed 22 Aug	0	0	0	0	0	33	671	1040	1140	775	663	599	667	747	683	921	1189	1481	1013	637	163	0	0	0	####
Thu 23 Aug	0	0	0	0	0	14	623	1055	1112	865	735	601	701	710	721	844	1155	1209	846	624	129	0	0	0	####
Fri 24 Aug	0	0	0	0	0	5	518	902	970	743	746	801	754	867	881	874	1021	1092	633	537	110	0	0	0	####
Sat 25 Aug	0	0	0	0	0	0	209	327	495	635	756	833	809	892	729	714	607	567	459	323	62	0	0	0	8417
Sun 26 Aug	0	0	0	0	0	0	100	233	369	437	549	440	436	478	477	380	366	252	259	235	40	0	0	0	5051
Mon 27 Aug	0	0	0	0	0	0	158	244	403	533	684	705	875	855	900	808	727	592	538	341	49	0	0	0	8412
Tue 28 Aug	0	0	0	0	0	0	498	1001	1103	835	714	715	762	826	875	1127	1286	1579	1028	691	54	0	0	0	####
Wed 29 Aug	0	0	0	0	0	0	572	1104	1093	763	652	644	680	746	840	988	1312	1574	1052	681	42	0	0	0	####
Thu 30 Aug	0	0	0	0	0	0	510	1010	1147	831	822	764	741	788	902	911	1157	1487	906	673	24	0	0	0	####
Fri 31 Aug	0	0	0	0	0	0	486	957	1157	770	728	838	841	895	1015	1078	1298	1178	757	506	8	0	0	0	####
Sat 1 Sep	0	0	0	0	0	0	171	420	470	650	662	717	847	743	759	767	706	596	526	382	0	0	0	0	8416
Sun 2 Sep	0	0	0	0	0	0	97	271	461	675	848	878	860	871	919	849	785	699	492	333	0	0	0	0	9038
Mon 3 Sep	0	0	0	0	0	0	441	1080	1202	749	663	621	665	774	784	890	968	1285	670	394	0	0	0	0	####
Tue 4 Sep	0	0	0	0	0	0	428	1183	1389	850	666	615	704	731	805	962	1283	1625	1012	557	0	0	0	0	####
Wed 5 Sep	0	0	0	0	0	0	423	1202	1504	824	727	678	897	737	861	1105	1395	1672	1135	559	0	0	0	0	####
Thu 6 Sep	0	0	0	0	0	0	410	1236	1643	945	869	694	784	685	805	1185	1361	1469	847	376	0	0	0	0	####
Fri 7 Sep	0	0	0	0	0	0	332	990	1119	578	486	447	551	665	686	814	938	1019	693	279	0	0	0	0	9598
Sat 8 Sep	0	0	0	0	0	0	122	348	480	569	684	671	705	705	633	580	514	514	509	224	0	0	0	0	7258
Sun 9 Sep	0	0	0	0	0	0	76	247	408	685	946	851	881	788	752	720	639	556	507	218	0	0	0	0	8274
Mon 10 Sep	0	0	0	0	0	0	312	1070	1428	798	620	607	646	700	755	1020	1246	1477	771	268	0	0	0	0	####
Tue 11 Sep	0	0	0	0	0	0	295	1119	1335	760	550	584	637	661	727	1023	1225	1473	1008	337	0	0	0	0	####
Wed 12 Sep	0	0	0	0	0	0	290	1232	1417	827	642	652	749	717	811	1008	1211	1565	972	294	0	0	0	0	####
Thu 13 Sep	0	0	0	0	0	0	273	1125	1519	909	668	737	667	719	769	1069	1226	1612	934	276	0	0	0	0	####
Fri 14 Sep	0	0	0	0	0	0	210	948	1378	746	584	572	599	719	861	891	928	1069	753	150	0	0	0	0	####
Sat 15 Sep	0	0	0	0	0	0	60	378	438	575	722	682	721	729	812	710	686	617	499	141	0	0	0	0	7770
Sun 16 Sep	0	0	0	0	0	0	36	195	330	462	470	723	644	671	719	871	736	497	429	105	0	0	0	0	6888
Mon 17 Sep	0	0	0	0	0	0	165	1133	1531	971	794	760	793	717	747	1040	1264	1498	989	154	0	0	0	0	####
Tue 18 Sep	0	0	0	0	0	0	148	1023	1216	651	544	529	514	580	751	781	1048	1457	943	126	0	0	0	0	####
Wed 19 Sep	0	0	0	0	0	0	112	964	1332	792	553	566	468	548	655	771	1050	1098	717	93	0	0	0	0	9719
Thu 20 Sep	0	0	0	0	0	0	104	998	1369	711	803	693	718	700	805	960	982	1212	668	63	0	0	0	0	####
Fri 21 Sep	0	0	0	0	0	0	63	786	1031	622	435	503	556	613	716	1007	884	902	624	48	0	0	0	0	8791
Sat 22 Sep	0	0	0	0	0	0	26	303	460	581	707	720	700	684	692	705	661	525	476	27	0	0	0	0	7267
Sun 23 Sep	0	0	0	0	0	0	13	212	283	494	659	723	770	829	808	698	687	623	460	12	0	0	0	0	7270
Mon 24 Sep	0	0	0	0	0	0	44	1127	1518	934	711	659	753	812	799	1061	1349	1534	965	0	0	0	0	0	####
Tue 25 Sep	0	0	0	0	0	0	20	1181	1588	987	778	774	793	783	839	1023	1279	1598	925	0	0	0	0	0	####
Wed 26 Sep	0	0	0	0	0	0	0	1103	1428	810	685	617	715	690	802	959	1187	1417	950	0	0	0	0	0	####
Thu 27 Sep	0	0	0	0	0	0	0	1072	1577	913	725	822	701	807	852	988	1328	1589	778	0	0	0	0	0	####
Fri 28 Sep	0	0	0	0	0	0	0	983	1421	854	774	803	929	1016	1017	1350	1366	1234	620	0	0	0	0	0	####
Sat 29 Sep	0	0	0	0	0	0	0	270	413	643	691	792	814	851	767	761	686	651	376	0	0	0	0	0	7715
Sun 30 Sep	0	0	0	0	0	0	0	162	350	521	710	812	900	746	698	613	635	502	321	0	0	0	0	0	6970
Mon 1 Oct	0	0	0	0	0	0	0	943	1632	1024	836	764	809	806	912	1091	1285	1624	678	0	0	0	0	0	####
Tue 2 Oct	0	0	0	0	0	0	0	826	1602	963	695	724	729	692	783	938	1399	1878	714	0	0	0	0	0	####
Wed 3 Oct	0	0	0	0	0	0	0	835	1476	936	661	696	668	787	802	926	1327	1690	630	0	0	0	0	0	####
Thu 4 Oct	0	0	0	0	0	0	0	822	1629	965	831	755	828	888	918	1091	1465	1690	550	0	0	0	0	0	####
Fri 5 Oct	0	0	0	0	0	0	0	528	1065	581	513	542	596	661	818	848	971	954	353	0	0	0	0	0	8430
Sat 6 Oct	0	0	0	0	0	0	0	154	400	543	610	650	721	782	779	727	732	671	255	0	0	0	0	0	7024
Sun 7 Oct	0	0	0	0	0	0	0	128	399	610	709	752	778	834	667	629	604	428	186	0	0	0	0	0	6724
Mon 8 Oct	0	0	0	0	0	0	0	638	1512	921	699	717	764	743	850	1062	1487	1757	436	0	0	0	0	0	####

Tue 9 Oct	0	0	0	0	0	0	0	545	1426	876	610	656	647	700	726	945	1316	1697	352	0	0	0	0	0	####
Wed 10 Oct	0	0	0	0	0	0	0	546	1491	981	876	861	873	912	982	1055	1399	1664	347	0	0	0	0	0	####
Thu 11 Oct	0	0	0	0	0	0	0	474	1500	860	617	602	719	730	753	1030	1302	1592	268	0	0	0	0	0	####
Fri 12 Oct	0	0	0	0	0	0	0	293	986	635	486	491	505	616	560	902	855	785	120	0	0	0	0	0	7234
Sat 13 Oct	0	0	0	0	0	0	0	81	275	283	301	314	353	398	420	403	426	384	78	0	0	0	0	0	3716
Sun 14 Oct	0	0	0	0	0	0	0	80	298	473	473	463	455	476	399	467	460	468	74	0	0	0	0	0	4585
Mon 15 Oct	0	0	0	0	0	0	0	364	1449	929	727	776	740	763	835	850	1189	1513	114	0	0	0	0	0	####
Tue 16 Oct	0	0	0	0	0	0	0	382	1499	906	679	702	721	723	813	1014	1398	1691	75	0	0	0	0	0	####
Wed 17 Oct	0	0	0	0	0	0	0	312	1507	857	752	748	794	875	876	1169	1463	1715	30	0	0	0	0	0	####
Thu 18 Oct	0	0	0	0	0	0	0	265	1371	849	635	719	769	791	872	1034	1232	1544	0	0	0	0	0	0	####
Fri 19 Oct	0	0	0	0	0	0	0	198	980	748	614	693	768	831	866	898	1057	1054	0	0	0	0	0	0	8708
Sat 20 Oct	0	0	0	0	0	0	0	47	352	460	481	628	657	718	703	652	601	474	0	0	0	0	0	0	5772
Sun 21 Oct	0	0	0	0	0	0	0	35	305	516	652	690	725	572	534	563	498	363	0	0	0	0	0	0	5452
Mon 22 Oct	0	0	0	0	0	0	0	132	1074	790	698	654	683	784	747	813	1036	1191	0	0	0	0	0	0	8602
Tue 23 Oct	0	0	0	0	0	0	0	76	836	527	396	451	513	509	510	555	791	702	0	0	0	0	0	0	5865
Wed 24 Oct	0	0	0	0	0	0	0	78	1083	775	652	659	695	707	732	899	1021	1016	0	0	0	0	0	0	8317
Thu 25 Oct	0	0	0	0	0	0	0	54	1076	777	643	692	713	735	708	876	779	0	0	0	0	0	0	0	7053
Fri 26 Oct	0	0	0	0	0	0	12	683	930	665	636	612	653	679	784	786	636	0	0	0	0	0	0	0	7076
Sat 27 Oct	0	0	0	0	0	0	0	125	221	175	182	309	437	434	448	466	255	0	0	0	0	0	0	0	3052
Sun 28 Oct	0	0	0	0	0	0	0	65	191	335	502	509	509	476	530	413	234	0	0	0	0	0	0	0	3764
Mon 29 Oct	0	0	0	0	0	0	0	642	1047	709	594	612	607	658	686	794	577	0	0	0	0	0	0	0	6926
Tue 30 Oct	0	0	0	0	0	0	0	660	1061	723	578	587	614	537	546	646	524	0	0	0	0	0	0	0	6476
Wed 31 Oct	0	0	0	0	0	0	0	686	1064	786	685	631	713	697	648	729	488	0	0	0	0	0	0	0	7127
Thu 1 Nov	0	0	0	0	0	0	0	526	787	592	462	463	672	629	659	707	424	0	0	0	0	0	0	0	5920
Fri 2 Nov	0	0	0	0	0	0	0	521	879	710	707	747	793	821	952	853	394	0	0	0	0	0	0	0	7377
Sat 3 Nov	0	0	0	0	0	0	0	177	290	351	496	561	566	517	563	406	184	0	0	0	0	0	0	0	4111
Sun 4 Nov	0	0	0	0	0	0	0	125	285	469	659	679	627	595	643	554	172	0	0	0	0	0	0	0	4808
Mon 5 Nov	0	0	0	0	0	0	0	575	1189	937	722	621	735	645	651	791	343	0	0	0	0	0	0	0	7209
Tue 6 Nov	0	0	0	0	0	0	0	543	1169	846	672	714	672	682	688	888	334	0	0	0	0	0	0	0	7208
Wed 7 Nov	0	0	0	0	0	0	0	509	1091	721	564	524	591	567	564	719	245	0	0	0	0	0	0	0	6095
Thu 8 Nov	0	0	0	0	0	0	0	460	1175	839	714	722	771	725	737	857	257	0	0	0	0	0	0	0	7257
Fri 9 Nov	0	0	0	0	0	0	0	373	915	710	583	627	724	689	697	762	182	0	0	0	0	0	0	0	6261
Sat 10 Nov	0	0	0	0	0	0	0	96	283	424	542	670	708	649	566	533	77	0	0	0	0	0	0	0	4548
Sun 11 Nov	0	0	0	0	0	0	0	77	277	508	570	532	631	496	441	405	66	0	0	0	0	0	0	0	4003
Mon 12 Nov	0	0	0	0	0	0	0	351	1122	811	677	615	664	719	655	800	118	0	0	0	0	0	0	0	6533
Tue 13 Nov	0	0	0	0	0	0	0	357	1149	887	727	609	640	612	690	784	102	0	0	0	0	0	0	0	6556
Wed 14 Nov	0	0	0	0	0	0	0	296	1083	693	530	512	619	596	553	692	71	0	0	0	0	0	0	0	5645
Thu 15 Nov	0	0	0	0	0	0	0	240	844	608	584	602	615	579	643	686	43	0	0	0	0	0	0	0	5444
Fri 16 Nov	0	0	0	0	0	0	0	163	706	495	379	445	531	550	555	540	14	0	0	0	0	0	0	0	4377
Sat 17 Nov	0	0	0	0	0	0	0	42	220	278	439	433	483	491	451	379	0	0	0	0	0	0	0	0	3216
Sun 18 Nov	0	0	0	0	0	0	0	26	255	294	501	498	518	505	421	351	0	0	0	0	0	0	0	0	3369
Mon 19 Nov	0	0	0	0	0	0	0	116	659	503	403	346	406	442	424	484	0	0	0	0	0	0	0	0	3782
Tue 20 Nov	0	0	0	0	0	0	0	81	577	413	326	316	306	328	309	395	0	0	0	0	0	0	0	0	3051
Wed 21 Nov	0	0	0	0	0	0	0	70	576	331	276	312	369	429	438	425	0	0	0	0	0	0	0	0	3226
Thu 22 Nov	0	0	0	0	0	0	0	63	699	378	297	268	312	285	385	428	0	0	0	0	0	0	0	0	3115
Fri 23 Nov	0	0	0	0	0	0	0	46	665	433	423	466	582	548	548	479	0	0	0	0	0	0	0	0	4191
Sat 24 Nov	0	0	0	0	0	0	0	13	269	350	444	485	469	488	520	406	0	0	0	0	0	0	0	0	3444
Sun 25 Nov	0	0	0	0	0	0	0	2	127	255	296	434	376	342	360	198	0	0	0	0	0	0	0	0	2390
Mon 26 Nov	0	0	0	0	0	0	0	10	740	492	427	418	445	458	478	391	0	0	0	0	0	0	0	0	3859

Tue 27 Nov	0	0	0	0	0	0	0	0	882	587	451	552	543	457	439	482	0	0	0	0	0	0	0	0	4393
Wed 28 Nov	0	0	0	0	0	0	0	0	665	449	357	324	351	326	351	382	0	0	0	0	0	0	0	0	3205
Thu 29 Nov	0	0	0	0	0	0	0	0	570	348	309	305	267	310	353	348	0	0	0	0	0	0	0	0	2810
Fri 30 Nov	0	0	0	0	0	0	0	0	559	456	380	451	553	502	513	483	0	0	0	0	0	0	0	0	3896
Sat 1 Dec	0	0	0	0	0	0	0	0	146	187	174	212	218	189	207	131	0	0	0	0	0	0	0	0	1464
Sun 2 Dec	0	0	0	0	0	0	0	0	94	198	269	268	290	282	311	187	0	0	0	0	0	0	0	0	1899
Mon 3 Dec	0	0	0	0	0	0	0	0	576	385	354	393	437	382	495	419	0	0	0	0	0	0	0	0	3441
Tue 4 Dec	0	0	0	0	0	0	0	0	549	360	314	296	372	404	374	439	0	0	0	0	0	0	0	0	3107
Wed 5 Dec	0	0	0	0	0	0	0	0	541	322	198	200	204	235	234	371	0	0	0	0	0	0	0	0	2304
Thu 6 Dec	0	0	0	0	0	0	0	0	744	491	333	320	398	348	432	483	0	0	0	0	0	0	0	0	3549
Fri 7 Dec	0	0	0	0	0	0	0	0	542	362	352	367	454	451	469	549	0	0	0	0	0	0	0	0	3547
Sat 8 Dec	0	0	0	0	0	0	0	0	97	180	242	321	302	402	314	205	0	0	0	0	0	0	0	0	2062
Sun 9 Dec	0	0	0	0	0	0	0	0	94	266	401	436	521	463	420	235	0	0	0	0	0	0	0	0	2836
Mon 10 Dec	0	0	0	0	0	0	0	0	532	460	423	342	420	364	452	382	0	0	0	0	0	0	0	0	3375
Tue 11 Dec	0	0	0	0	0	0	0	0	566	475	382	430	405	431	479	497	0	0	0	0	0	0	0	0	3665
Wed 12 Dec	0	0	0	0	0	0	0	0	551	511	389	407	463	426	483	357	0	0	0	0	0	0	0	0	3587
Thu 13 Dec	0	0	0	0	0	0	0	0	433	411	316	336	403	438	414	304	0	0	0	0	0	0	0	0	3054
Fri 14 Dec	0	0	0	0	0	0	0	0	349	321	304	350	400	432	457	355	0	0	0	0	0	0	0	0	2969
Sat 15 Dec	0	0	0	0	0	0	0	0	59	166	177	199	256	188	218	105	0	0	0	0	0	0	0	0	1367
Sun 16 Dec	0	0	0	0	0	0	0	0	31	153	217	250	270	279	281	131	0	0	0	0	0	0	0	0	1612
Mon 17 Dec	0	0	0	0	0	0	0	0	315	313	249	251	319	344	292	317	0	0	0	0	0	0	0	0	2399
Tue 18 Dec	0	0	0	0	0	0	0	0	240	248	170	184	225	209	210	278	0	0	0	0	0	0	0	0	1764
Wed 19 Dec	0	0	0	0	0	0	0	0	264	320	312	292	274	316	343	339	0	0	0	0	0	0	0	0	2460
Thu 20 Dec	0	0	0	0	0	0	0	0	253	347	251	307	316	354	329	291	0	0	0	0	0	0	0	0	2449
Fri 21 Dec	0	0	0	0	0	0	0	0	181	230	227	275	341	329	319	241	0	0	0	0	0	0	0	0	2143
Sat 22 Dec	0	0	0	0	0	0	0	0	66	166	255	305	294	291	367	182	0	0	0	0	0	0	0	0	1926
Sun 23 Dec	0	0	0	0	0	0	0	0	41	158	199	222	218	217	222	126	0	0	0	0	0	0	0	0	1403
Mon 24 Dec	0	0	0	0	0	0	0	0	67	181	232	271	304	282	250	177	0	0	0	0	0	0	0	0	1764
Tue 25 Dec	0	0	0	0	0	0	0	0	11	29	50	79	82	46	62	40	0	0	0	0	0	0	0	0	398
Wed 26 Dec	0	0	0	0	0	0	0	0	26	115	202	232	269	233	243	107	0	0	0	0	0	0	0	0	1427
Thu 27 Dec	0	0	0	0	0	0	0	0	61	139	171	264	379	325	323	174	0	0	0	0	0	0	0	0	1836
Fri 28 Dec	0	0	0	0	0	0	0	0	62	163	205	266	277	275	270	186	0	0	0	0	0	0	0	0	1703
Sat 29 Dec	0	0	0	0	0	0	0	0	26	80	96	142	155	169	203	146	0	0	0	0	0	0	0	0	1017
Sun 30 Dec	0	0	0	0	0	0	0	0	30	113	163	210	243	231	225	138	0	0	0	0	0	0	0	0	1353
Mon 31 Dec	0	0	0	0	0	0	0	0	47	137	230	336	298	255	267	177	0	0	0	0	0	0	0	0	1747

Appendix D: Darkness Traffic flow

Hour Ending	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Total
Mon 1 Jan	29	18	13	10	9	18	15	39	31.7	0	0	0	0	0	0	37.8	124	122	93	92	66	64	31	17	830
Tue 2 Jan	8	10	10	67	16	38	85	200	154	0	0	0	0	0	0	34	293	354	204	123	58	62	42	21	1779
Wed 3 Jan	16	2	3	4	8	24	93	205	167	0	0	0	0	0	0	41.3	338	515	241	150	107	74	51	19	2058
Thu 4 Jan	21	6	7	7	19	42	118	290	165	0	0	0	0	0	0	23.4	300	416	251	120	100	64	49	17	2015
Fri 5 Jan	16	15	4	1	16	53	112	290	174	0	0	0	0	0	0	37.4	399	494	265	176	97	75	105	45	2374
Sat 6 Jan	35	14	13	12	15	37	38	78	53.8	0	0	0	0	0	0	26.2	217	226	195	191	139	134	59	25	1508
Sun 7 Jan	16	13	6	9	9	16	22	47	44.6	0	0	0	0	0	0	14.6	263	244	192	171	137	85	54	17	1360
Mon 8 Jan	14	5	5	4	25	66	149	290	178	0	0	0	0	0	0	10.9	477	586	339	204	131	107	67	42	2700
Tue 9 Jan	22	15	6	7	40	79	209	393	259	0	0	0	0	0	0	0	432	570	334	212	150	90	85	40	2943
Wed 10 Jan	20	14	15	11	31	73	184	420	205	0	0	0	0	0	0	0	488	604	353	222	153	79	76	49	2997
Thu 11 Jan	19	18	9	10	22	67	178	461	227	0	0	0	0	0	0	0	440	597	364	211	164	98	73	48	3006
Fri 12 Jan	25	29	16	8	40	54	229	534	227	0	0	0	0	0	0	0	452	592	346	203	139	114	86	53	3147
Sat 13 Jan	25	20	18	15	30	48	62	89	48.8	0	0	0	0	0	0	0	217	245	239	181	152	115	92	36	1633
Sun 14 Jan	22	26	10	8	13	25	39	61	40.3	0	0	0	0	0	0	0	165	202	155	242	120	66	42	30	1267
Mon 15 Jan	7	17	9	11	24	53	170	336	184	0	0	0	0	0	0	0	402	654	385	255	149	109	84	63	2912
Tue 16 Jan	13	14	10	17	34	72	176	344	156	0	0	0	0	0	0	0	399	547	372	237	159	119	72	48	2789
Wed 17 Jan	14	15	20	5	30	64	137	257	101	0	0	0	0	0	0	0	268	434	343	208	144	101	109	63	2314
Thu 18 Jan	24	17	13	17	28	36	121	189	76.9	0	0	0	0	0	0	0	283	384	244	180	142	83	77	46	1961
Fri 19 Jan	36	22	44	20	58	78	182	453	110	0	0	0	0	0	0	0	289	441	302	210	163	115	78	46	2646
Sat 20 Jan	30	20	28	13	32	36	61	87	40.9	0	0	0	0	0	0	0	195	226	196	213	159	101	65	38	1541
Sun 21 Jan	20	10	15	18	13	19	24	28	18.3	0	0	0	0	0	0	0	55.9	93	101	122	95	82	58	30	802
Mon 22 Jan	19	11	14	14	24	53	142	244	92	0	0	0	0	0	0	0	295	583	359	272	173	145	79	47	2566
Tue 23 Jan	29	16	27	16	23	85	255	468	149	0	0	0	0	0	0	0	401	1022	571	350	266	179	234	63	4154
Wed 24 Jan	39	27	20	12	28	91	203	324	97.6	0	0	0	0	0	0	0	321	765	503	354	239	145	106	74	3348
Thu 25 Jan	27	22	29	20	34	104	224	461	96.2	0	0	0	0	0	0	0	365	818	471	290	209	147	104	83	3504
Fri 26 Jan	35	19	18	19	30	85	236	495	77.6	0	0	0	0	0	0	0	302	586	414	252	186	135	79	61	3030
Sat 27 Jan	36	29	27	46	34	58	94	121	22.1	0	0	0	0	0	0	0	143	235	230	207	137	92	67	51	1629
Sun 28 Jan	50	16	13	17	11	29	35	57	9.36	0	0	0	0	0	0	0	109	267	241	223	162	93	50	35	1417
Mon 29 Jan	25	16	15	14	36	89	249	539	37	0	0	0	0	0	0	0	283	953	531	305	218	175	144	75	3704
Tue 30 Jan	39	20	22	20	29	106	330	614	16.2	0	0	0	0	0	0	0	313	994	654	338	261	180	116	73	4125
Wed 31 Jan	37	22	15	22	27	95	274	618	0	0	0	0	0	0	0	0	239	960	646	295	231	155	174	88	3898
Thu 1 Feb	50	61	29	31	40	97	307	598	0	0	0	0	0	0	0	0	215	953	705	387	302	173	145	109	4202
Fri 2 Feb	61	83	23	29	33	223	365	703	0	0	0	0	0	0	0	0	249	985	735	508	361	332	233	278	5201
Sat 3 Feb	72	52	35	42	53	103	101	103	0	0	0	0	0	0	0	0	70.4	279	230	186	133	106	70	61	1696
Sun 4 Feb	108	91	67	123	27	32	48	77.4	0	0	0	0	0	0	0	0	76.5	352	435	333	232	124	97	52	2275
Mon 5 Feb	27	18	15	18	27	83	267	439	0	0	0	0	0	0	0	0	124	901	532	344	270	167	115	64	3411
Tue 6 Feb	21	21	24	24	36	99	243	381	0	0	0	0	0	0	0	0	72.2	712	426	358	193	155	134	53	2952
Wed 7 Feb	23	20	13	13	51	73	220	351	0	0	0	0	0	0	0	0	44.4	743	475	278	223	151	108	103	2889
Thu 8 Feb	24	20	24	13	29	101	273	380	0	0	0	0	0	0	0	0	19.8	710	419	239	187	126	70	77	2712
Fri 9 Feb	49	68	56	41	61	118	378	416	0	0	0	0	0	0	0	0	0	637	394	290	213	154	118	132	3125
Sat 10 Feb	42	25	25	29	37	110	145	103	0	0	0	0	0	0	0	0	0	239	253	189	126	95	66	42	1525
Sun 11 Feb	35	19	16	28	24	46	55	59.9	0	0	0	0	0	0	0	0	0	257	233	209	178	119	85	59	1423
Mon 12 Feb	25	25	29	41	51	134	352	277	0	0	0	0	0	0	0	0	0	760	481	345	226	167	149	95	3156
Tue 13 Feb	57	36	31	31	49	120	332	297	0	0	0	0	0	0	0	0	0	623	423	252	158	131	126	66	2732
Wed 14 Feb	44	54	39	15	56	149	313	258	0	0	0	0	0	0	0	0	0	548	396	242	176	116	149	92	2647

Thu 15 Feb	38	22	44	23	57	137	349	263	0	0	0	0	0	0	0	0	0	646	560	328	213	154	152	98	3084
Fri 16 Feb	55	38	50	26	54	125	367	265	0	0	0	0	0	0	0	0	0	554	526	321	197	153	131	127	2989
Sat 17 Feb	43	26	25	37	43	110	149	74.8	0	0	0	0	0	0	0	0	0	266	325	253	170	135	95	80	1832
Sun 18 Feb	45	28	27	27	24	48	70	53.2	0	0	0	0	0	0	0	0	0	248	301	221	189	120	80	51	1532
Mon 19 Feb	33	21	29	23	43	128	309	208	0	0	0	0	0	0	0	0	0	577	567	309	244	204	148	102	2945
Tue 20 Feb	49	41	24	38	37	129	419	228	0	0	0	0	0	0	0	0	0	637	656	412	285	190	154	127	3426
Wed 21 Feb	46	47	38	31	62	148	425	197	0	0	0	0	0	0	0	0	0	586	648	409	288	206	181	162	3474
Thu 22 Feb	47	24	56	26	43	111	387	155	0	0	0	0	0	0	0	0	0	526	659	389	271	222	167	152	3236
Fri 23 Feb	50	60	47	16	46	122	339	127	0	0	0	0	0	0	0	0	0	385	435	299	256	176	134	138	2630
Sat 24 Feb	46	43	39	49	44	101	137	32.3	0	0	0	0	0	0	0	0	0	156	330	292	203	180	98	80	1831
Sun 25 Feb	58	37	30	43	23	46	82	14.2	0	0	0	0	0	0	0	0	0	159	296	286	247	151	89	40	1601
Mon 26 Feb	37	33	26	26	56	126	343	47.1	0	0	0	0	0	0	0	0	0	345	547	316	292	164	150	122	2630
Tue 27 Feb	72	114	30	8	35	92	189	8.7	0	0	0	0	0	0	0	0	0	179	388	223	152	117	93	62	1762
Wed 28 Feb	49	42	40	26	58	66	132	0	0	0	0	0	0	0	0	0	0	55.7	127	107	102	46	42	55	948
Thu 1 Mar	25	20	16	17	21	61	121	0	0	0	0	0	0	0	0	0	0	45.6	113	70	60	76	48	32	726
Fri 2 Mar	25	25	20	21	22	53	86.4	0	0	0	0	0	0	0	0	0	0	40	116	93	71	47	47	47	713
Sat 3 Mar	33	23	22	23	32	52	58.1	0	0	0	0	0	0	0	0	0	0	27.4	116	114	81	69	56	37	744
Sun 4 Mar	27	21	7	16	23	35	17.6	0	0	0	0	0	0	0	0	0	0	21.1	105	94	112	88	76	61	704
Mon 5 Mar	20	25	17	10	21	78	134	0	0	0	0	0	0	0	0	0	0	112	519	282	199	167	124	82	1790
Tue 6 Mar	38	40	39	19	31	101	146	0	0	0	0	0	0	0	0	0	0	73.8	517	345	224	213	163	114	2064
Wed 7 Mar	52	52	52	23	55	129	265	0	0	0	0	0	0	0	0	0	0	75.5	673	408	297	217	215	155	2669
Thu 8 Mar	74	47	58	39	42	130	248	0	0	0	0	0	0	0	0	0	0	29.5	636	385	262	205	223	152	2531
Fri 9 Mar	65	73	72	54	49	136	255	0	0	0	0	0	0	0	0	0	0	0	536	323	263	231	169	156	2382
Sat 10 Mar	57	39	37	30	30	104	78.1	0	0	0	0	0	0	0	0	0	0	0	250	204	169	126	86	66	1276
Sun 11 Mar	53	30	14	40	24	70	50	0	0	0	0	0	0	0	0	0	0	0	310	237	233	177	124	92	1454
Mon 12 Mar	57	33	39	43	53	174	208	0	0	0	0	0	0	0	0	0	0	0	536	346	257	194	196	160	2296
Tue 13 Mar	71	54	61	47	74	179	231	0	0	0	0	0	0	0	0	0	0	0	693	459	334	253	240	144	2841
Wed 14 Mar	104	80	59	51	72	166	221	0	0	0	0	0	0	0	0	0	0	0	645	473	300	228	228	191	2818
Thu 15 Mar	78	62	62	66	59	166	163	0	0	0	0	0	0	0	0	0	0	0	422	294	234	182	132	117	2037
Fri 16 Mar	62	65	48	36	50	126	87.3	0	0	0	0	0	0	0	0	0	0	0	297	302	207	168	126	136	1711
Sat 17 Mar	32	26	28	39	52	89	35.8	0	0	0	0	0	0	0	0	0	0	0	125	155	113	120	84	46	944
Sun 18 Mar	21	34	29	29	33	38	11.4	0	0	0	0	0	0	0	0	0	0	0	91	138	135	88	92	47	786
Mon 19 Mar	43	41	92	97	92	113	59.8	0	0	0	0	0	0	0	0	0	0	0	312	284	251	177	177	135	1873
Tue 20 Mar	49	63	40	29	54	135	54.1	0	0	0	0	0	0	0	0	0	0	0	440	394	298	247	189	136	2128
Wed 21 Mar	70	43	75	51	69	146	42.3	0	0	0	0	0	0	0	0	0	0	0	386	369	252	167	180	135	1986
Thu 22 Mar	65	38	66	28	76	154	14.2	0	0	0	0	0	0	0	0	0	0	0	413	439	312	222	191	157	2175
Fri 23 Mar	53	71	34	57	205	291	0	0	0	0	0	0	0	0	0	0	0	0	346	552	334	247	232	192	2614
Sat 24 Mar	84	139	72	40	43	125	0	0	0	0	0	0	0	0	0	0	0	0	212	260	241	147	103	71	1537
Sun 25 Mar	56	0	39	92	90	47.8	0	0	0	0	0	0	0	0	0	0	0	0	190	322	273	171	114	108	1503
Mon 26 Mar	38	63	38	33	99	157	0	0	0	0	0	0	0	0	0	0	0	0	444	598	348	262	221	174	2476
Tue 27 Mar	141	53	49	24	59	136	0	0	0	0	0	0	0	0	0	0	0	0	299	451	313	279	196	155	2156
Wed 28 Mar	66	95	43	37	130	263	0	0	0	0	0	0	0	0	0	0	0	0	340	483	392	258	213	169	2489
Thu 29 Mar	108	78	62	61	112	191	314	0	0	0	0	0	0	0	0	0	0	0	0	215	528	339	263	287	2558
Fri 30 Mar	72	73	34	20	25	64	75.6	0	0	0	0	0	0	0	0	0	0	0	0	71.4	175	193	110	69	982
Sat 31 Mar	50	36	36	32	30	68	59.2	0	0	0	0	0	0	0	0	0	0	0	0	37.5	140	115	76	64	744
Sun 1 Apr	44	27	22	23	34	45	32.2	0	0	0	0	0	0	0	0	0	0	0	0	45.8	146	151	125	110	805
Mon 2 Apr	44	18	30	17	29	45	45	0	0	0	0	0	0	0	0	0	0	0	0	42	125	91	104	47	637
Tue 3 Apr	66	31	32	26	52	136	201	0	0	0	0	0	0	0	0	0	0	0	0	72.2	333	241	265	163	1618

Wed 4 Apr	61	57	29	36	50	122	204	0	0	0	0	0	0	0	0	0	0	0	0	40.8	135	118	127	125	1105
Thu 5 Apr	26	15	9	93	27	63	67.1	0	0	0	0	0	0	0	0	0	0	0	0	31.9	141	121	54	46	694
Fri 6 Apr	28	26	10	19	63	76	75.6	0	0	0	0	0	0	0	0	0	0	0	0	14.7	112	92	64	48	628
Sat 7 Apr	31	17	10	12	36	49	27.8	0	0	0	0	0	0	0	0	0	0	0	0	3.5	61	59	37	29	372
Sun 8 Apr	21	11	7	11	11	17	22.1	0	0	0	0	0	0	0	0	0	0	0	0	3.64	109	66	41	42	362
Mon 9 Apr	22	5	7	12	28	101	63.6	0	0	0	0	0	0	0	0	0	0	0	0	0	170	88	64	51	611
Tue 10 Apr	18	14	14	11	29	62	26.9	0	0	0	0	0	0	0	0	0	0	0	0	0	66.5	61	35	35	372
Wed 11 Apr	23	16	34	34	69	70	32.2	0	0	0	0	0	0	0	0	0	0	0	0	0	74.4	64	43	32	492
Thu 12 Apr	20	11	15	16	30	74	26.1	0	0	0	0	0	0	0	0	0	0	0	0	0	56.7	55	44	27	375
Fri 13 Apr	17	11	18	8	20	50	14.5	0	0	0	0	0	0	0	0	0	0	0	0	0	69.6	74	32	43	357
Sat 14 Apr	27	14	9	11	26	47	5.88	0	0	0	0	0	0	0	0	0	0	0	0	0	68.9	70	42	29	350
Sun 15 Apr	33	16	10	13	9	31	1.23	0	0	0	0	0	0	0	0	0	0	0	0	0	63.2	59	30	15	280
Mon 16 Apr	11	14	15	12	26	94	0	0	0	0	0	0	0	0	0	0	0	0	0	0	85.5	87	92	42	478
Tue 17 Apr	18	18	14	9	28	93.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	121	61	34	496
Wed 18 Apr	32	21	20	17	30	93.8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	137	106	63	37	556
Thu 19 Apr	25	21	19	9	26	60.9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	134	98	53	28	474
Fri 20 Apr	86	84	48	46	65	164	0	0	0	0	0	0	0	0	0	0	0	0	0	0	304	327	218	211	1553
Sat 21 Apr	102	98	69	40	50	118	0	0	0	0	0	0	0	0	0	0	0	0	0	0	229	307	154	179	1345
Sun 22 Apr	73	58	77	36	36	52.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	200	273	186	110	1101
Mon 23 Apr	59	45	44	41	50	156	0	0	0	0	0	0	0	0	0	0	0	0	0	0	####	275	276	205	####
Tue 24 Apr	77	62	38	41	57	143	0	0	0	0	0	0	0	0	0	0	0	0	0	0	164	242	246	179	1249
Wed 25 Apr	99	75	56	46	64	133	0	0	0	0	0	0	0	0	0	0	0	0	0	0	233	360	324	220	1610
Thu 26 Apr	92	73	65	36	69	109	0	0	0	0	0	0	0	0	0	0	0	0	0	0	191	362	304	234	1535
Fri 27 Apr	113	97	79	64	67	106	0	0	0	0	0	0	0	0	0	0	0	0	0	0	200	325	263	220	1534
Sat 28 Apr	77	63	58	41	53	54.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	94.7	253	175	112	981
Sun 29 Apr	86	38	41	30	32	31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	140	219	174	113	904
Mon 30 Apr	75	56	48	33	67	83.3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	140	291	246	197	1236
Tue 1 May	70	63	51	32	56	92.8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	132	380	229	220	1325
Wed 2 May	69	100	48	51	60	63.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	105	295	269	216	1277
Thu 3 May	123	79	38	36	59	56.4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	90.2	314	242	215	1253
Fri 4 May	69	73	45	43	64	53.4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	81.4	357	220	272	1278
Sat 5 May	102	64	51	46	39	31.9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50.6	226	189	142	941
Sun 6 May	81	52	45	38	21	15.8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	44	262	183	128	870
Mon 7 May	79	66	63	37	36	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	37.2	346	264	136	1082
Tue 8 May	94	77	66	54	67	33.8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20.2	339	280	239	1270
Wed 9 May	100	93	51	43	50	39.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11.8	315	266	194	1163
Thu 10 May	94	80	37	27	55	23.4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	364	297	242	1219
Fri 11 May	114	71	64	45	66	15.4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	308	295	206	1185
Sat 12 May	81	42	52	69	57	6.7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	218	173	140	838
Sun 13 May	90	68	46	34	23	1.16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	258	201	114	835
Mon 14 May	75	72	36	50	59.8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	342	322	227	1184
Tue 15 May	98	93	29	30	72.8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	332	326	286	1266
Wed 16 May	73	60	47	50	64.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	301	302	221	1118
Thu 17 May	54	38	24	31	39.6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	119	105	86	496
Fri 18 May	34	43	21	24	29.9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	114	104	92	462
Sat 19 May	33	38	25	23	22.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	92	101	61	395
Sun 20 May	45	33	31	20	9.96	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	80.5	73	41	333
Mon 21 May	36	28	18	17	29.6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	114	124	105	471

Tue 22 May	42	21	23	22	26.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	68.9	106	86	395
Wed 23 May	106	46	16	26	-672	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	86.2	106	98	-188
Thu 24 May	41	20	24	23	21.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	69.6	116	82	397
Fri 25 May	33	42	20	25	21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50.7	80	84	356
Sat 26 May	21	23	15	15	17.7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	44.6	90	50	276
Sun 27 May	20	25	7	11	8.71	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	63.4	57	52	244
Mon 28 May	31	12	13	23	15.6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	62.5	89	62	308
Tue 29 May	29	23	12	12	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	51.7	80	60	281
Wed 30 May	17	22	14	19	16.8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	42.8	81	36	249
Thu 31 May	32	20	20	14	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	62.4	79	66	311
Fri 1 Jun	97	112	62	43	44.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	176	303	239	1076
Sat 2 Jun	130	81	61	61	32.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	80.6	134	99	679
Sun 3 Jun	81	68	35	119	51.4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	89.9	179	129	752
Mon 4 Jun	65	63	54	121	32.3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	118	276	213	942
Tue 5 Jun	100	94	74	35	35.4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	140	301	233	1012
Wed 6 Jun	98	96	37	50	37.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	124	273	177	893
Thu 7 Jun	86	81	57	36	37	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	127	299	205	928
Fri 8 Jun	95	85	40	49	37.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	96	282	253	938
Sat 9 Jun	235	125	123	51	34.8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	80.6	172	145	966
Sun 10 Jun	91	79	75	77	22.6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	73.7	170	133	721
Mon 11 Jun	115	56	59	109	56.7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	63.5	262	164	885
Tue 12 Jun	106	69	49	47	56.3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	86.7	288	245	947
Wed 13 Jun	96	92	58	89	74.7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	74.4	245	163	892
Thu 14 Jun	79	67	45	29	29.7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	62.6	247	170	729
Fri 15 Jun	105	97	90	91	36.6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	65.6	219	182	886
Sat 16 Jun	73	55	43	38	20.6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	33.7	139	104	506
Sun 17 Jun	94	40	36	36	15.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	32.6	148	115	517
Mon 18 Jun	88	127	61	102	27.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	68	250	204	928
Tue 19 Jun	49	74	43	173	74	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	53	250	174	890
Wed 20 Jun	92	110	63	46	29.7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	48.3	288	219	896
Thu 21 Jun	94	88	165	146	68.9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	64.3	262	231	1119
Fri 22 Jun	138	120	36	50	30.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	61.5	257	260	953
Sat 23 Jun	108	130	90	141	28.4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	41	216	121	875
Sun 24 Jun	110	68	60	140	25.4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	54.1	231	129	818
Mon 25 Jun	84	57	59	86	56.7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	70	261	231	905
Tue 26 Jun	47	81	44	137	38.4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	58	267	225	897
Wed 27 Jun	78	79	25	41	34.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	86.4	319	247	909
Thu 28 Jun	103	105	50	96	54.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	68.5	342	214	1033
Fri 29 Jun	93	75	84	48	41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	63.7	256	186	847
Sat 30 Jun	74	129	88	53	31.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	46.1	196	124	741
Sun 1 Jul	89	58	33	34	22.4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	44.5	210	117	608
Mon 2 Jul	46	45	64	57	38.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	71.8	244	163	729
Tue 3 Jul	69	65	156	100	79.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	63.6	434	240	1207
Wed 4 Jul	124	108	58	42	44.7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	81.6	303	192	953
Thu 5 Jul	80	87	77	44	32.4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	80.3	270	228	899
Fri 6 Jul	87	85	61	45	42.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	77.5	254	250	902
Sat 7 Jul	92	105	45	73	53.6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	74.8	193	130	766
Sun 8 Jul	136	101	51	42	26.7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	58.6	155	99	669

Mon 9 Jul	68	45	38	20	34.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	89.6	248	166	709
Tue 10 Jul	75	73	57	31	42.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	112	316	229	935
Wed 11 Jul	100	86	67	28	41.3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	93.8	379	226	1021
Thu 12 Jul	99	78	71	57	42.3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	118	308	201	974
Fri 13 Jul	95	90	43	45	40.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	130	263	216	922
Sat 14 Jul	158	81	94	73	35.4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	114	207	125	888
Sun 15 Jul	75	53	49	36	16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	98.4	175	98	600
Mon 16 Jul	59	34	28	39	38.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	110	265	166	740
Tue 17 Jul	61	40	63	38	35.7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	147	264	225	874
Wed 18 Jul	74	51	45	44	47.9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	155	267	212	896
Thu 19 Jul	84	95	72	35	64.8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	178	360	259	1148
Fri 20 Jul	122	79	63	132	114	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	139	206	208	1063
Sat 21 Jul	109	66	46	37	56.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	140	177	146	778
Sun 22 Jul	83	63	52	21	44.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	144	148	99	654
Mon 23 Jul	46	29	14	27	60	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	172	192	109	649
Tue 24 Jul	52	30	20	21	39	5.61	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	208	186	141	703
Wed 25 Jul	48	41	30	12	58	9.4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	265	239	156	859
Thu 26 Jul	64	42	31	25	53	15.7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	238	222	138	829
Fri 27 Jul	73	100	42	26	66	19.3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	140	152	131	749
Sat 28 Jul	45	56	32	29	46	17.7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	128	112	91	557
Sun 29 Jul	62	44	43	26	38	9.86	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	141	98	81	543
Mon 30 Jul	48	33	16	20	33	37.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	197	118	111	614
Tue 31 Jul	65	34	26	28	43	47.6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	257	176	110	786
Wed 1 Aug	62	27	27	22	46	49.4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	220	164	116	734
Thu 2 Aug	55	27	34	27	60	53.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	302	208	139	905
Fri 3 Aug	73	51	31	31	48	49.6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	220	149	136	788
Sat 4 Aug	83	74	83	46	56	48.3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	235	150	101	876
Sun 5 Aug	92	63	43	33	37	49.8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	220	146	95	778
Mon 6 Aug	51	35	27	25	53	90.7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10.4	308	228	188	1016
Tue 7 Aug	82	66	46	32	71	87.3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	27.3	359	262	176	1209
Wed 8 Aug	101	64	52	35	84	98.7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	40	329	231	209	1244
Thu 9 Aug	104	75	43	40	86	113	0	0	0	0	0	0	0	0	0	0	0	0	0	0	60.4	334	291	181	1327
Fri 10 Aug	93	75	47	43	59	95.4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	54.9	234	175	171	1047
Sat 11 Aug	59	74	57	21	46	77.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	51.2	164	152	84	785
Sun 12 Aug	62	30	30	22	29	25.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	52.7	182	122	80	635
Mon 13 Aug	54	75	22	21	58	94.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	96.9	215	204	146	986
Tue 14 Aug	66	74	45	34	67	142	0	0	0	0	0	0	0	0	0	0	0	0	0	0	125	297	215	149	1214
Wed 15 Aug	94	78	51	36	73	141	0	0	0	0	0	0	0	0	0	0	0	0	0	0	104	211	178	153	1119
Thu 16 Aug	90	55	45	45	71	135	0	0	0	0	0	0	0	0	0	0	0	0	0	0	158	281	210	170	1261
Fri 17 Aug	168	95	46	51	87	197	0	0	0	0	0	0	0	0	0	0	0	0	0	0	155	257	192	160	1408
Sat 18 Aug	79	68	53	65	57	110	0	0	0	0	0	0	0	0	0	0	0	0	0	0	138	243	152	155	1120
Sun 19 Aug	95	74	35	29	42	52.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	149	186	190	107	959
Mon 20 Aug	109	53	43	92	101	235	0	0	0	0	0	0	0	0	0	0	0	0	0	0	175	253	203	194	1459
Tue 21 Aug	87	69	36	38	75	190	0	0	0	0	0	0	0	0	0	0	0	0	0	0	307	331	245	194	1572
Wed 22 Aug	108	69	98	114	139	294	0	0	0	0	0	0	0	0	0	0	0	0	0	0	265	296	230	149	1763

Thu 23 Aug	79	80	43	31	65	179	0	0	0	0	0	0	0	0	0	0	0	0	0	0	240	261	193	182	1353
Fri 24 Aug	111	87	39	40	58	157	0	0	0	0	0	0	0	0	0	0	0	0	0	0	256	242	184	153	1327
Sat 25 Aug	81	35	32	30	49	93	0	0	0	0	0	0	0	0	0	0	0	0	0	0	166	180	117	84	867
Sun 26 Aug	59	50	30	22	19	47	3.09	0	0	0	0	0	0	0	0	0	0	0	0	0	140	144	96	59	669
Mon 27 Aug	50	39	35	37	44	94	11.9	0	0	0	0	0	0	0	0	0	0	0	0	0	224	230	176	94	1035
Tue 28 Aug	60	52	43	32	44	195	67.9	0	0	0	0	0	0	0	0	0	0	0	0	0	362	267	224	155	1502
Wed 29 Aug	80	73	32	49	54	172	78	0	0	0	0	0	0	0	0	0	0	0	0	0	381	293	200	200	1612
Thu 30 Aug	87	66	45	39	69	201	90	0	0	0	0	0	0	0	0	0	0	0	0	0	448	230	226	185	1686
Fri 31 Aug	92	77	39	49	75	189	107	0	0	0	0	0	0	0	0	0	0	0	0	0	400	280	195	186	1689
Sat 1 Sep	68	67	48	52	51	147	48.2	0	0	0	0	0	0	0	0	0	0	0	0	11.8	294	186	114	120	1207
Sun 2 Sep	91	57	48	40	29	96	32.3	0	0	0	0	0	0	0	0	0	0	0	0	25.1	353	206	136	86	1199
Mon 3 Sep	53	44	22	36	57	166	172	0	0	0	0	0	0	0	0	0	0	0	0	53.8	243	184	159	111	1300
Tue 4 Sep	66	68	35	41	57	215	202	0	0	0	0	0	0	0	0	0	0	0	0	98.3	439	288	230	135	1874
Wed 5 Sep	96	65	51	40	69	199	228	0	0	0	0	0	0	0	0	0	0	0	0	140	407	272	227	153	1946
Thu 6 Sep	89	76	47	44	54	199	241	0	0	0	0	0	0	0	0	0	0	0	0	112	351	243	177	148	1781
Fri 7 Sep	88	74	58	35	64	221	222	0	0	0	0	0	0	0	0	0	0	0	0	109	335	224	167	123	1719
Sat 8 Sep	72	45	46	48	45	103	92	0	0	0	0	0	0	0	0	0	0	0	0	106	286	170	138	127	1278
Sun 9 Sep	76	52	39	31	32	77	67.2	0	0	0	0	0	0	0	0	0	0	0	0	128	259	170	136	89	1156
Mon 10 Sep	43	81	23	19	46	194	312	0	0	0	0	0	0	0	0	0	0	0	0	178	270	161	168	124	1619
Tue 11 Sep	55	53	25	35	48	171	333	0	0	0	0	0	0	0	0	0	0	0	0	276	322	256	236	157	1967
Wed 12 Sep	81	48	51	35	109	269	385	0	0	0	0	0	0	0	0	0	0	0	0	272	383	256	206	140	2234
Thu 13 Sep	92	85	33	34	60	199	377	0	0	0	0	0	0	0	0	0	0	0	0	311	339	208	219	174	2131
Fri 14 Sep	108	80	25	40	69	199	342	0	0	0	0	0	0	0	0	0	0	0	0	208	263	217	167	144	1862
Sat 15 Sep	60	44	31	36	67	129	111	0	0	0	0	0	0	0	0	0	0	0	0	230	258	182	109	82	1339
Sun 16 Sep	55	76	49	47	49	72	77.5	0	0	0	0	0	0	0	0	0	0	0	0	212	261	157	113	101	1270
Mon 17 Sep	64	43	34	34	56	181	426	0	0	0	0	0	0	0	0	0	0	0	0	360	289	234	190	181	2091
Tue 18 Sep	89	93	36	27	57	202	444	0	0	0	0	0	0	0	0	0	0	0	0	379	257	215	250	196	2245
Wed 19 Sep	91	69	42	42	64	202	398	0	0	0	0	0	0	0	0	0	0	0	0	329	291	192	193	139	2052
Thu 20 Sep	85	69	52	65	118	229	414	0	0	0	0	0	0	0	0	0	0	0	0	309	278	192	146	177	2134
Fri 21 Sep	99	68	49	41	51	121	309	0	0	0	0	0	0	0	0	0	0	0	0	356	289	230	179	153	1944
Sat 22 Sep	97	71	60	65	90	115	172	0	0	0	0	0	0	0	0	0	0	0	0	308	234	188	129	130	1659
Sun 23 Sep	108	85	81	88	68	77	113	0	0	0	0	0	0	0	0	0	0	0	0	374	261	189	126	87	1657
Mon 24 Sep	72	55	45	32	59	176	585	0	0	0	0	0	0	0	0	0	0	0	0	582	298	265	230	157	2556
Tue 25 Sep	66	68	51	34	67	229	631	0	0	0	0	0	0	0	0	0	0	0	48.7	569	344	267	188	154	2717
Wed 26 Sep	95	57	36	56	44	225	586	0	0	0	0	0	0	0	0	0	0	0	82.6	558	332	238	228	179	2717
Thu 27 Sep	104	72	49	39	66	201	594	33.2	0	0	0	0	0	0	0	0	0	0	116	548	402	274	258	175	2931
Fri 28 Sep	94	69	64	72	51	175	579	74	0	0	0	0	0	0	0	0	0	0	136	558	357	271	199	187	2886
Sat 29 Sep	74	89	60	57	45	107	206	23.4	0	0	0	0	0	0	0	0	0	0	106	431	351	227	121	106	2003
Sun 30 Sep	56	55	41	54	31	75	114	22.1	0	0	0	0	0	0	0	0	0	0	119	324	294	206	105	82	1578
Mon 1 Oct	41	36	26	37	65	177	606	166	0	0	0	0	0	0	0	0	0	0	291	423	299	200	217	165	2749
Tue 2 Oct	75	50	30	33	60	178	597	181	0	0	0	0	0	0	0	0	0	0	385	563	411	280	227	161	3231
Wed 3 Oct	91	55	36	30	55	195	597	235	0	0	0	0	0	0	0	0	0	0	386	517	370	235	213	155	3170
Thu 4 Oct	100	66	29	31	63	188	561	274	0	0	0	0	0	0	0	0	0	0	415	642	403	286	228	170	3456
Fri 5 Oct	102	76	37	31	67	135	421	205	0	0	0	0	0	0	0	0	0	0	313	458	336	267	189	154	2791
Sat 6 Oct	91	66	85	124	62	129	155	72.3	0	0	0	0	0	0	0	0	0	0	276	420	340	213	196	115	2344
Sun 7 Oct	80	67	31	41	35	71	134	69	0	0	0	0	0	0	0	0	0	0	227	352	222	190	106	90	1715
Mon 8 Oct	59	289	176	22	53	168	536	391	0	0	0	0	0	0	0	0	0	0	654	594	418	320	211	165	4056
Tue 9 Oct	88	41	26	24	43	190	536	394	0	0	0	0	0	0	0	0	0	0	600	535	389	258	232	167	3523
Wed 10 Oct	63	53	55	37	75	196	557	447	0	0	0	0	0	0	0	0	0	0	738	563	372	314	220	178	3868

Thu 11 Oct	92	68	30	45	55	184	536	420	0	0	0	0	0	0	0	0	0	0	688	530	373	273	213	150	3658
Fri 12 Oct	114	58	40	29	53	148	367	293	0	0	0	0	0	0	0	0	0	0	403	398	263	204	141	111	2621
Sat 13 Oct	75	58	35	45	47	99	128	98.5	0	0	0	0	0	0	0	0	0	0	312	278	215	156	116	97	1759
Sun 14 Oct	86	44	44	45	48	60	101	105	0	0	0	0	0	0	0	0	0	0	360	374	229	149	114	104	1864
Mon 15 Oct	70	27	28	33	47	169	547	546	0	0	0	0	0	0	0	0	0	0	833	542	357	234	202	136	3771
Tue 16 Oct	63	57	31	43	70	185	579	650	0	0	0	0	0	0	0	0	0	0	861	536	344	288	231	148	4086
Wed 17 Oct	86	48	38	38	62	178	538	633	0	0	0	0	0	0	0	0	0	0	971	521	362	262	201	144	4082
Thu 18 Oct	71	54	33	32	50	164	458	618	0	0	0	0	0	0	0	0	0	0	965	550	358	280	203	160	3996
Fri 19 Oct	88	68	39	45	84	137	443	537	0	0	0	0	0	0	0	0	0	32.6	658	455	299	238	195	199	3517
Sat 20 Oct	95	74	66	37	43	136	154	156	0	0	0	0	0	0	0	0	0	41.2	411	370	274	169	119	96	2242
Sun 21 Oct	99	71	52	96	36	84	120	138	0	0	0	0	0	0	0	0	0	49.4	343	338	272	162	133	105	2099
Mon 22 Oct	40	21	16	24	48	131	436	645	0	0	0	0	0	0	0	0	0	210	867	481	324	246	224	138	3851
Tue 23 Oct	49	47	29	29	34	113	309	505	0	0	0	0	0	0	0	0	0	175	674	372	260	180	179	101	3057
Wed 24 Oct	44	34	26	28	39	138	472	699	0	0	0	0	0	0	0	0	0	304	857	514	269	236	240	145	4045
Thu 25 Oct	62	34	38	28	40	133	401	716	0	0	0	0	0	0	0	0	288	1335	805	499	337	236	223	158	5333
Fri 26 Oct	91	58	39	31	57	133	382	0	0	0	0	0	0	0	0	0	273	852	605	361	282	213	165	183	3725
Sat 27 Oct	66	71	23	41	56	62	99	0	0	0	0	0	0	0	0	0	125	366	387	398	285	225	76	63	2343
Sun 28 Oct	54	64	17	18	21	36	78	2.01	0	0	0	0	0	0	0	0	143	330	324	287	240	109	86	65	1874
Mon 29 Oct	37	41	31	15	40	101	422	48.3	0	0	0	0	0	0	0	0	418	1156	710	406	311	202	185	150	4273
Tue 30 Oct	56	48	27	50	73	153	436	90	0	0	0	0	0	0	0	0	429	1126	685	465	318	295	203	197	4651
Wed 31 Oct	62	58	25	33	45	127	391	121	0	0	0	0	0	0	0	0	451	1049	641	426	266	179	132	137	4143
Thu 1 Nov	68	73	33	57	44	114	391	115	0	0	0	0	0	0	0	0	459	964	661	403	294	257	170	127	4231
Fri 2 Nov	69	80	53	37	59	135	382	147	0	0	0	0	0	0	0	0	482	857	602	378	277	211	194	182	4145
Sat 3 Nov	89	104	57	170	141	117	145	59	0	0	0	0	0	0	0	0	253	371	339	268	171	140	117	112	2653
Sun 4 Nov	40	39	25	18	25	60	121	48.4	0	0	0	0	0	0	0	0	281	407	377	293	252	155	83	47	2271
Mon 5 Nov	36	27	23	82	43	149	403	270	0	0	0	0	0	0	0	0	638	1199	672	412	295	243	132	148	4772
Tue 6 Nov	60	48	23	38	64	151	440	292	0	0	0	0	0	0	0	0	711	1274	795	463	338	254	201	117	5269
Wed 7 Nov	60	59	31	37	54	141	406	312	0	0	0	0	0	0	0	0	631	1078	642	399	275	215	177	132	4649
Thu 8 Nov	56	64	28	39	63	138	436	333	0	0	0	0	0	0	0	0	770	1214	797	486	324	207	183	130	5268
Fri 9 Nov	77	46	33	37	37	113	349	305	0	0	0	0	0	0	0	0	644	839	562	410	242	143	130	96	4063
Sat 10 Nov	32	28	24	23	32	87	106	88.3	0	0	0	0	0	0	0	0	352	410	393	306	255	172	112	81	2501
Sun 11 Nov	55	36	46	74	108	106	99	83.7	0	0	0	0	0	0	0	0	322	406	319	293	204	141	98	59	2450
Mon 12 Nov	42	28	21	20	41	125	447	430	0	0	0	0	0	0	0	0	792	1157	804	414	305	193	177	114	5109
Tue 13 Nov	61	62	28	32	39	143	426	492	0	0	0	0	0	0	0	0	914	1231	893	472	307	253	185	136	5675
Wed 14 Nov	59	41	26	31	52	93	360	483	0	0	0	0	0	0	0	0	816	1007	700	409	274	217	167	105	4840
Thu 15 Nov	36	30	22	18	39	105	313	447	0	0	0	0	0	0	0	0	808	936	645	338	202	162	119	95	4315
Fri 16 Nov	29	28	30	14	33	106	272	346	0	0	0	0	0	0	0	0	662	685	453	295	225	162	107	66	3513
Sat 17 Nov	33	26	28	19	23	49	87	109	0	0	0	0	0	0	0	0	282	280	263	218	142	86	108	50	1803
Sun 18 Nov	33	23	16	26	15	40	43	78	0	0	0	0	0	0	0	10.9	259	214	199	211	165	111	70	43	1557
Mon 19 Nov	32	10	18	18	27	83	263	410	0	0	0	0	0	0	0	25.5	609	750	467	297	212	149	105	59	3535
Tue 20 Nov	25	40	8	15	26	72	223	367	0	0	0	0	0	0	0	29.8	582	678	458	249	165	114	75	73	3200
Wed 21 Nov	20	35	18	7	24	101	197	340	0	0	0	0	0	0	0	47.2	606	685	462	307	211	128	96	66	3351
Thu 22 Nov	36	29	26	21	28	85	265	425	0	0	0	0	0	0	0	47.5	488	696	407	289	192	172	95	61	3362
Fri 23 Nov	42	20	22	21	30	93	260	417	0	0	0	0	0	0	0	71.6	693	697	430	308	205	143	106	88	3646
Sat 24 Nov	58	25	26	19	40	71	105	173	0	0	0	0	0	0	0	83.1	375	325	308	224	165	159	101	77	2334
Sun 25 Nov	40	24	26	27	22	40	72	71.8	0	0	0	0	0	0	0	43.4	249	229	232	177	134	117	57	45	1606
Mon 26 Nov	10	17	11	5	31	88	275	484	0	0	0	0	0	0	0	97.8	724	825	580	329	217	150	100	70	4014
Tue 27 Nov	30	30	32	11	22	86	310	628	18	0	0	0	0	0	0	136	757	831	515	263	157	144	90	53	4113
Wed 28 Nov	21	13	12	19	36	77	232	449	35	0	0	0	0	0	0	114	545	666	451	251	174	122	101	77	3395
Thu 29 Nov	23	21	11	15	35	81	220	408	42.9	0	0	0	0	0	0	116	509	628	398	251	164	117	83	56	3179

Fri 30 Nov	20	18	14	9	21	93	216	451	62.1	0	0	0	0	0	0	178	859	769	430	241	178	130	98	44	3832
Sat 1 Dec	40	23	24	27	20	52	81	88	25.8	0	0	0	0	0	0	48.3	194	203	203	166	107	86	80	29	1497
Sun 2 Dec	25	22	18	19	26	36	48	55	16.7	0	0	0	0	0	0	69.1	225	170	171	167	118	77	52	32	1347
Mon 3 Dec	33	8	6	13	32	74	258	506	127	0	0	0	0	0	0	179	831	816	523	318	226	144	103	54	4251
Tue 4 Dec	45	25	22	23	33	103	250	412	137	0	0	0	0	0	0	206	876	1000	512	325	199	130	113	73	4485
Wed 5 Dec	27	30	22	25	33	90	211	416	161	0	0	0	0	0	0	174	798	708	394	212	152	112	105	59	3730
Thu 6 Dec	47	24	23	22	27	90	270	597	248	0	0	0	0	0	0	238	977	1247	518	350	220	177	110	92	5277
Fri 7 Dec	49	25	23	22	26	59	235	416	181	0	0	0	0	0	0	271	831	652	396	235	179	150	111	71	3931
Sat 8 Dec	40	32	48	17	28	45	95	90	41.4	0	0	0	0	0	0	110	283	248	272	213	122	90	68	48	1891
Sun 9 Dec	25	19	18	22	18	29	46	84	44.2	0	0	0	0	0	0	127	276	217	271	198	164	124	72	60	1814
Mon 10 Dec	29	23	12	11	21	63	230	468	262	0	0	0	0	0	0	205	768	954	588	346	209	155	126	75	4545
Tue 11 Dec	29	25	20	13	25	79	274	469	305	0	0	0	0	0	0	268	1010	1365	595	314	194	164	132	100	5381
Wed 12 Dec	42	56	25	21	40	113	297	584	324	0	0	0	0	0	0	210	712	926	561	295	221	120	93	83	4723
Thu 13 Dec	39	48	28	22	42	90	258	464	265	0	0	0	0	0	0	178	550	758	463	216	209	101	127	92	3951
Fri 14 Dec	47	26	21	11	31	76	235	378	233	0	0	0	0	0	0	209	458	468	302	202	145	103	90	70	3104
Sat 15 Dec	29	14	21	5	12	51	52	86	42.4	0	0	0	0	0	0	61.4	115	97	86	50	36	30	38	22	848
Sun 16 Dec	12	4	18	7	15	19	31	32	23.7	0	0	0	0	0	0	70.4	155	139	128	89	110	49	58	25	985
Mon 17 Dec	17	10	8	10	23	68	202	376	257	0	0	0	0	0	0	170	503	503	326	138	122	63	97	71	2965
Tue 18 Dec	32	36	16	20	32	82	222	370	212	0	0	0	0	0	0	150	385	435	275	159	96	68	110	89	2789
Wed 19 Dec	36	22	10	23	25	71	254	428	234	0	0	0	0	0	0	182	506	562	341	208	129	95	102	84	3312
Thu 20 Dec	45	39	16	20	37	67	233	373	234	0	0	0	0	0	0	144	423	464	324	203	148	98	96	79	3042
Fri 21 Dec	52	54	20	25	44	65	219	282	168	0	0	0	0	0	0	118	353	321	236	145	111	99	46	45	2403
Sat 22 Dec	23	15	18	17	18	42	52	73	66	0	0	0	0	0	0	85.4	175	174	154	110	94	48	57	26	1247
Sun 23 Dec	13	12	9	28	11	24	29	33	40.5	0	0	0	0	0	0	54	160	104	81	61	66	35	34	26	821
Mon 24 Dec	14	6	10	7	12	20	40	85	72.3	0	0	0	0	0	0	75.9	167	128	89	58	41	30	19	14	888
Tue 25 Dec	2	1	2	2	6	2	7	16	11.4	0	0	0	0	0	0	15.4	37	39	28	31	25	9	11	7	252
Wed 26 Dec	5	4	1	4	4	11	14	32	28.1	0	0	0	0	0	0	39.7	120	112	50	44	45	28	25	6	573
Thu 27 Dec	10	5	3	5	8	22	51	96	66	0	0	0	0	0	0	58	173	184	90	59	37	39	37	11	954
Fri 28 Dec	9	4	4	7	13	16	44	85	67.1	0	0	0	0	0	0	55.4	178	129	85	74	39	24	20	8	862
Sat 29 Dec	17	10	7	11	11	24	31	46	28.1	0	0	0	0	0	0	41.1	125	111	70	66	67	32	30	14	741
Sun 30 Dec	4	4	1	6	9	13	16	38	32.2	0	0	0	0	0	0	34.6	125	78	67	49	35	24	13	9	558
Mon 31 Dec	9	2	13	35	40	46	50	55	50.4	0	0	0	0	0	0	38.9	156	104	89	35	30	29	11	15	808

Appendix E: Yearly precipitation

Hour Ending	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16	P17	P18	P19	P20	P21	P22	P23	P24	PTotal
Mon 1 Jan	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tue 2 Jan	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.55	0.55	0.00	0.00	0.00	0.00	0.00	0.00	2.1	4.9	5.3	1.35	17.75
Wed 3 Jan	0.15	1.8	3.8	0.9	3.1	5.1	1.5	0.9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	17.25
Thu 4 Jan	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.4	4.5	5.1	2.6	2	0.9	3	9.2	5.75	1.1	1.2	1.2	0.6	0.3	0.00	38.85
Fri 5 Jan	0.00	0.00	0.00	0.96	1.14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.67	7.48	2.85	1.27	14.37
Sat 6 Jan	1.91	0.725	0.00	0.00	0.00	0.6	1.6	0.4	0.00	0.9	0.00	0.00	0.00	0.00	0.3	1.2	0.00	0.00	0.00	0.5	0.1	0.00	0.00	0.00	8.24
Sun 7 Jan	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mon 8 Jan	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tue 9 Jan	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wed 10 Jan	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thu 11 Jan	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.8	2.25	5.35	2.65	0.15	1.2	0.6	0.00	0.00	0.00	13.00
Fri 12 Jan	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sat 13 Jan	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.9	0.9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.80
Sun 14 Jan	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mon 15 Jan	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1	0.00	0.00	0.00	0.00	1.2	0.3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.48	3.22	9.20
Tue 16 Jan	0.94	1.96	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.40
Wed 17 Jan	0.00	0.00	0.00	0.00	0.00	0.00	2.36	0.25	0.00	0.00	0.9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.3	2.23	6.04
Thu 18 Jan	7.67	0.6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.3	14.3	15	17.9	36.8	20.5	4.8	1.74	1.86	0.00	0.00	0.00	0.00	0.00	0.00	124.47
Fri 19 Jan	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	7.36	6.54	0.00	0.00	0.00	13.90
Sat 20 Jan	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sun 21 Jan	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.3	3.94	3.08	0.18	10.50
Mon 22 Jan	2.52	4.14	0.24	0.5	2.2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	9.60
Tue 23 Jan	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wed 24 Jan	0.00	0.00	0.00	0.00	0.00	3.64	28.4	14	11.8	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	57.82
Thu 25 Jan	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fri 26 Jan	0.00	0.00	0.00	4.9	1.1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	6.00
Sat 27 Jan	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	6.00
Sun 28 Jan	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.1	4.18	1.32	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	9.60
Mon 29 Jan	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tue 30 Jan	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wed 31 Jan	0.00	0.00	0.00	0.00	4.3	2.3	3	0.00	0.00	2.04	1.56	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	13.20
January Average	0.44	0.31	0.13	0.24	0.25	0.31	1.13	0.69	0.53	0.26	0.69	0.67	0.84	1.37	0.75	0.38	0.74	0.34	0.04	0.34	0.48	0.56	0.51	0.28	12.29
Thu 1 Feb	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fri 2 Feb	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sat 3 Feb	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.94	0.66	0.78	4.4	2.1	4.74	3.38	4.4	1.26	3.3	2.64	0.00	0.00	0.00	0.00	0.00	0.00	30.60
Sun 4 Feb	4.8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.22	1.68	1.14	0.00	0.00	0.00	0.00	0.48	2.82	0.00	0.00	0.00	0.00	0.00	13.14
Mon 5 Feb	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tue 6 Feb	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.44	16.8	7.5	2.3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	32.00
Wed 7 Feb	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		3.3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.30
Thu 8 Feb	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.26	4.4	13	0.00	0.00	0.00	18.70
Fri 9 Feb	0.00	0.00	0.00	0.00	0.00	0.00	2.9	9.29	2.16	4.58	14	3.5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	36.45
Sat 10 Feb	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.56	2.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.12	15.8	8.6	6.6	39.70
Sun 11 Feb	4.76	20.34	23.7	8.3	0.3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	57.40
Mon 12 Feb	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Tue 13 Feb	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.9	5.2	9	1.8	3.12	3.18	3.1	1.8	1.5	0	0	0.00	0.00	0.00	0.00	0.00	29.60
Wed 14 Feb	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0	2.9	4	3.12	0.48	0	2.4	1.2	1.74	1.56	0.00	0.00	17.40
Thu 15 Feb	0.00	0.00	0.00	3.8	11.5	2.4	0	3.18	0.42	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	21.30
Fri 16 Feb	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sat 17 Feb	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sun 18 Feb	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mon 19 Feb	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	19.6	47.7	6.96	1.74	1.2	2.1	0	3.4	3.6	1.44	87.74
Tue 20 Feb	0.66	0.00	2.58	3.74	0.78	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	7.76
Wed 21 Feb	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thu 22 Feb	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fri 23 Feb	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sat 24 Feb	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sun 25 Feb	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mon 26 Feb	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tue 27 Feb	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wed 28 Feb	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
February Average	0.365	0.726	0.939	0.566	0.449	0.086	0.1	0.55	0.15	0.43	1.13	0.32	0.32	0.55	1.83	2.19	0.52	0.17	0.27	0.28	0.71	0.74	0.44	0.29	14.1104
Thu 1 Mar	0.00	3.06	0.54	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.60
Fri 2 Mar	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sat 3 Mar	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sun 4 Mar	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.52	3.48	5.2	9.1	12.2	15.7	14.1	3.54	2.76	0.00	0.00	0.00	0.00	0.00	0.00	2.34	70.94
Mon 5 Mar	0.54	15.8	10.86	2.4	3.74	5.9	3.3	0.00	0.00	0.00	0.00	2.88	0.72	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	46.14
Tue 6 Mar	0.00	4.1	9	19.78	27.72	36.56	21.4	4.2	8.2	3.3	2.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	136.34
Wed 7 Mar	0.00	0.00	0.00	0.00	0.00	0.00	2.58	1.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.66
Thu 8 Mar	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fri 9 Mar	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sat 10 Mar	1.80	5.4	8.2	9.6	14.3	16.04	11.3	5.6	11.8	9.3	0.9	0	1.44	2.16	7.2	10.7	0	0	1.74	6.06	2	2.58	1.02		129.18
Sun 11 Mar	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mon 12 Mar	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0	5.9	7.1	5.6	5	3.74	4.6	3.6	2.94	1.32	0.00	0.00	0.00	0.00	0.00	39.80
Tue 13 Mar	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wed 14 Mar	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thu 15 Mar	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0	3.5	14.3	18.1	20.1	17.7	11.9	0.48	0	1.44	2.16	0.84	2.46	92.96
Fri 16 Mar	0.00	0.00	4.26	3.21	6.8	15.1	15.4	5.6	4.6	3.96	5.2	4.5	0	3.12	0.48	2.16	1.74	7.8	6.34	0.78	7.06	8.2	4.7	0.3	111.27
Sat 17 Mar	0.00	3	0.6	2.1	1.5	6.4	6.9	0.9	7.4	7.8	5	3.1	2.4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	47.10
Sun 18 Mar	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mon 19 Mar	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0	1.92	1.68	0	0.06	3.54	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	7.20
Tue 20 Mar	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wed 21 Mar	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.3	0.3	0.00	0.00	0.00	3.60
Thu 22 Mar	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0	0.6	2.1	2.70
Fri 23 Mar	0.00	0	1.32	2.28	0	0	3.24	0.84	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	7.68
Sat 24 Mar	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sun 25 Mar	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mon 26 Mar	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tue 27 Mar	0.00	0.00	0.00	0.72	5.08	12.3	14	4	0.24	0.00	0.00	0.00	3	0.6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	39.90
Wed 28 Mar	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thu 29 Mar	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fri 30 Mar	0.00	0	4.1	17.1	12.9	5.5	5.6	4.2	0	0	1.86	1.74	0	0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	53.00

Sat 31 Mar	0.00	0.00	0.00	3.1	18.52	27.18	10.9	3	2.94	9.6	16.3	16	13.5	16.2	11.7	3.4	0.00	0.00	0.00	3.48	3.36	0.36		0.28	159.82
March Average	0.075	1.012	1.254	1.945	2.921	4.032	3.05	0.95	1.28	1.26	1.37	1.43	1.48	1.84	1.78	1.43	0.83	0.73	0.32	0.44	0.46	0.43	0.24	0.25	30.8029
Sun 1 Apr	10.32	1.82	4.6	0.78	0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.88	0.72	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	21.12
Mon 2 Apr	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.4	15	13.9	12.6	14.6	15.9	18.9	15.5	11.1	10.6	4.04	7.2	1.8	6.5	17.9	5.14	1.56	175.70
Tue 3 Apr	0.00	0.00	3.18	0.42	0.00	0.00	0.00	1.26	2.34	0.00	0.00	0.00	0.00	0.42	7.68	6	2.4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	23.70
Wed 4 Apr	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.42	3.18	3.4	4.8	4.3	0	1.2	2.1	0.12	31.4	25.9	41.4	45.6	32.9	10.7	3.94	3.2	214.58
Thu 5 Apr	0.00	2.4	1.2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.42	0.18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	7.20
Fri 6 Apr	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sat 7 Apr	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.7	6.3	17.7	10.9	2.64	1.74	0.00	0.00	0.00	0.00	0.00	0.00	43.00
Sun 8 Apr	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mon 9 Apr	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tue 10 Apr	0.00	0.00	0.00		0	17.8	25	26.5	66.1	81.3	115	109	17.8	0	2.4	12.3	0	9.75	4.05				0.45	4.35	491.10
Wed 11 Apr	0.00	0.00	0.00	7.05	0.45	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	7.50
Thu 12 Apr	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.1	16.8	5.1	0.06	0.9	5.31	28.23
Fri 13 Apr	0.09	0.00	0.00	0.00	0.00	8.06	11.9	1.68		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	21.69
Sat 14 Apr	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sun 15 Apr	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0	0.96	3.3	2.64	6.90
Mon 16 Apr	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0	3.36	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.60
Tue 17 Apr	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wed 18 Apr	0.00	0.00	0	2.5	0.8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.30
Thu 19 Apr	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fri 20 Apr	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sat 21 Apr	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0	9.62	14.5	1.6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	25.70
Sun 22 Apr	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0	2.52	1.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.60
Mon 23 Apr	0.00	0.00	0.00	0.00	0.00	0.00	0	2.1	3.9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	6.00
Tue 24 Apr	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wed 25 Apr	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thu 26 Apr	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fri 27 Apr	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sat 28 Apr	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sun 29 Apr	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mon 30 Apr	0.00	2.82	0.48	0.00	0.00	0.00	0.00	0.00	0	3.42	0.18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	6.90
April Average	0.347	0.235	0.315	0.371	0.042	0.862	1.23	1.18	3.12	3.72	4.89	4.42	1.54	0.96	1.51	1.35	1.57	1.38	1.76	2.21	1.53	1.02	0.46	0.57	36.3273
Tue 1 May	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wed 2 May	0.00	0.00	0.00	0.00	0.00	0	2.22	1.38	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.60
Thu 3 May	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fri 4 May	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sat 5 May	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sun 6 May	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mon 7 May	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tue 8 May	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wed 9 May	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.5	0.50
Thu 10 May	4.34	4.6	5.04	1.6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	15.58
Fri 11 May	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sat 12 May	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.5	4.5	0.00	0.00	2.6	8.60
Sun 13 May	14.70	10.6	5	13.22	13.4	16.32	6.68	0.42		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	80.34

Mon 14 May	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tue 15 May	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wed 16 May	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thu 17 May	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fri 18 May	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sat 19 May	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sun 20 May	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mon 21 May	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tue 22 May	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wed 23 May	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thu 24 May	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fri 25 May	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sat 26 May	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sun 27 May	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mon 28 May	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tue 29 May	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wed 30 May	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thu 31 May	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
May Average	0.614	0.49	0.324	0.478	0.432	0.526	0.29	0.06	0	0	0	0	0	0	0	0	0	0	0	0.05	0.15	0	0	0.1	3.50387
Fri 1 Jun	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sat 2 Jun	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0	5.8	28.6	45.4	14.1	12.6	2.9	109.37
Sun 3 Jun	2.16	1.44	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.60
Mon 4 Jun	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tue 5 Jun	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wed 6 Jun	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thu 7 Jun	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fri 8 Jun	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sat 9 Jun	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sun 10 Jun	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0	12.9	29.6	0.24	0.00	0.00	0.00	0.00	0.00	0.00	42.70
Mon 11 Jun	0.00	0.00	0.00	0.00	0.00	1.86	1.44	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.30
Tue 12 Jun	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wed 13 Jun	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0	0.36	6.64	11.1	0.84	18.90
Thu 14 Jun	1.50	0.00	0.00	0.00	0.00	0.06	3.54	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.10
Fri 15 Jun	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sat 16 Jun	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0	3.8	2.8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	6.60
Sun 17 Jun	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mon 18 Jun	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tue 19 Jun	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	3.24	3.36	0.24	0.00	0.00	6.90
Wed 20 Jun	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thu 21 Jun	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fri 22 Jun	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sat 23 Jun	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sun 24 Jun	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mon 25 Jun	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tue 26 Jun	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wed 27 Jun	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thu 28 Jun	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

	Fri 29 Jun	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Sat 30 Jun	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
June Average		0.122	0.048	0	0	0	0.064	0.17	0	0	0	0	0	0	0	0	0	0.56	1.08	0.2	1.06	1.64	0.7	0.79	0.12	6.549
	Sun 1 Jul	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mon 2 Jul	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Tue 3 Jul	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Wed 4 Jul	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Thu 5 Jul	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Fri 6 Jul	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Sat 7 Jul	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Sun 8 Jul	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mon 9 Jul	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Tue 10 Jul	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Wed 11 Jul	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Thu 12 Jul	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Fri 13 Jul	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Sat 14 Jul	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Sun 15 Jul	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mon 16 Jul	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0	0.96	10.5	11.5	5.44	1.6	0.00	0.00	0.00	0.00	0.00	0.5	32.1	41.9	104.42
	Tue 17 Jul	24.04	0.24	0	0.66	2.94	0	0	3.36	0.24	0	0	0	2.16	1.44	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	35.08
	Wed 18 Jul	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Thu 19 Jul	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Fri 20 Jul	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Sat 21 Jul	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Sun 22 Jul	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mon 23 Jul	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Tue 24 Jul	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0	2.46	1.14	0.00	0.00	0.00	0.00	0.00	3.60
	Wed 25 Jul	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Thu 26 Jul	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Fri 27 Jul	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.36	3.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.9	40.4	8.8	0.00	57.70
	Sat 28 Jul	0.00	0.00	0.00	0.00	0.00	0.66	2.94	0.00	0.00	3.1	15.2	12.8	0	3.36	0.24	0	0	28.3	0.00	0.00	0.00	0.00	0.00	0.00	66.60
	Sun 29 Jul	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mon 30 Jul	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1	37.4	7.5	0.00	0.00	0.00	0.00	45.90
	Tue 31 Jul	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
July Average		0.775	0.008	0	0.021	0.095	0.021	0.09	0.11	0.01	0.1	0.5	0.55	0.41	0.53	0.18	0.05	0	1.02	1.24	0.24	0.16	1.32	1.32	1.35	10.1065
	Wed 1 Aug	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0	5.46	12.6	0.54	0	2.8	3.6	1.2	26.20
	Thu 2 Aug	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Fri 3 Aug	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.56	5.1	21.1	6.98	5.16	2.1	9.84	4.5	0.00	10.7	1.1	0.00	0.00	0.00	0.00	0.00	68.10
	Sat 4 Aug	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.36	3.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.60
	Sun 5 Aug	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mon 6 Aug	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Tue 7 Aug	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Wed 8 Aug	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Thu 9 Aug	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Fri 10 Aug	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Sat 11 Aug	0.00	0.00	2.16	1.44	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	6.60
Sun 12 Aug	3.30	4.6	1.9	0	7.36	9.2	6.9	23.4	3	5.3	4.58	2.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	71.83
Mon 13 Aug	11.60	6.3	11	20.5	0.9	6.5	2.7	0	0.00	0.00	0.00	0.00	0.00	29.9	29.9	0.84	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	120.18
Tue 14 Aug	6.60	2.1	0.00	0.00	0.00	0.00	3	10	10	3.6	0.00	0.00	0.00	14	0	2.46	1.14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	52.94
Wed 15 Aug	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thu 16 Aug	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fri 17 Aug	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sat 18 Aug	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sun 19 Aug	0.96	3	11.02	22.5	16.1	14.3	4.2	1.86	1.74	0.00	0.00	0.00	0.36	3.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	79.28
Mon 20 Aug	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.56	5.44	3.04	3.3	3.1	16.4	9.9	42.74
Tue 21 Aug	2.40	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.86	1.74	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	6.00
Wed 22 Aug	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thu 23 Aug	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.36	13	2.4	0.00	0.00	0.00	0.00	0.00	20.80
Fri 24 Aug	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sat 25 Aug	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.36	1	13.8	0.24	0.00	0.00	0.00	0.00	18.36
Sun 26 Aug	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.76	3.54	3.7	2.1	9.86	3.8	2.04	0.00	0.00	0.00	0.00	0.00	0.00	27.80
Mon 27 Aug	0.00	1.86	1.74	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.60
Tue 28 Aug	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wed 29 Aug	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thu 30 Aug	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fri 31 Aug	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
August Average	0.802	0.576	0.897	1.434	0.786	0.968	0.54	1.14	0.6	0.61	0.83	0.48	0.29	1.71	1.35	0.57	0.44	1.09	1.14	0.12	0.11	0.19	0.65	0.36	17.6781
Sat 1 Sep	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sun 2 Sep	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mon 3 Sep	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0	9.5	11.7	7.95	4.16	4.44	4.4	1.16	0.84	0.00	44.10
Tue 4 Sep	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wed 5 Sep	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thu 6 Sep	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.3	2.1	0.00	0.00	0.00	0.00	0.00	6.40
Fri 7 Sep	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.66	5.4	2.44	4.36	3.24	0	16.4	15.2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	47.70
Sat 8 Sep	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.86	4.4	0.54	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	6.80
Sun 9 Sep	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mon 10 Sep	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.36	3.24	0	0.36	3	0	6.96
Tue 11 Sep	14.70	11.26	3.8	1.8	2.64	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	34.20
Wed 12 Sep	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thu 13 Sep	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fri 14 Sep	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.2	2.9	4.10
Sat 15 Sep	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sun 16 Sep	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.96	2.64	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.60
Mon 17 Sep	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tue 18 Sep	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.25	4.25	0.54	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	6.04
Wed 19 Sep	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0	9.2	9.1	4.4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	22.70
Thu 20 Sep	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.66	16.5	30	19.3	4.16	3.64	8.5	31.6	16.3	130.65
Fri 21 Sep	17.80	6.4	15.6	33.96	45.74	20.4	3	1.14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	144.04
Sat 22 Sep	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sun 23 Sep	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.96	5.2	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	6.40

Mon 24 Sep	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tue 25 Sep	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wed 26 Sep	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thu 27 Sep	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fri 28 Sep	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sat 29 Sep	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sun 30 Sep	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
September Average	1.083	0.589	0.647	1.192	1.613	0.68	0.1	0.13	0.5	0.11	0.15	0.11	0	0.91	0.96	0.54	1.03	1.41	0.87	0.39	0.27	0.33	1.22	0.64	15.4563
Mon 1 Oct	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tue 2 Oct	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wed 3 Oct	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thu 4 Oct	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.06
Fri 5 Oct	3.24	3.7	2.8	12.6	5.7	3.06	5.04	12.6	4.6	3.4	2.78	4.03	0.4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	63.94
Sat 6 Oct	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sun 7 Oct	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mon 8 Oct	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tue 9 Oct	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wed 10 Oct	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thu 11 Oct	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fri 12 Oct	0.00	0.00	0.00	0.00	0.00	0	2.9	10.7	1.14	0.00	0.00	0	4.76	1.14	0.00	0.00	0.00	0.00	0	2.94	0.84	12.5	23.2	1.9	61.98
Sat 13 Oct	3.06	0.54	2.94	0.84	1.26	2.34	3.24	0.54	8.54	8.5	14.3	8.64	4.54	0.54	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.56	1.74	63.14
Sun 14 Oct	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0	1.56	2.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.60
Mon 15 Oct	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.26	2.34	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.60
Tue 16 Oct	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wed 17 Oct	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thu 18 Oct	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fri 19 Oct	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sat 20 Oct	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sun 21 Oct	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mon 22 Oct	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tue 23 Oct	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0	3.38	2.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.63
Wed 24 Oct	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thu 25 Oct	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fri 26 Oct	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.36	2.94	0.00	0.00	0.00	3.30
Sat 27 Oct	0.00	0.00	0.00	0.00	1.7	14.26	17.5	7.5	6.5	10.7	4.58	0.53	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0	3.8	2.6	0	69.70
Sun 28 Oct	0.00	0.00	0.06	2.64	0	4.6	5.1	3.1	2.76	0.84	0.00	0.00	0.00	0.00	0	0.66	2.94	0	0.66	2.94	0	0	0	0	26.30
Mon 29 Oct	5.20	4.8	0.00	0.00	0.00	1.56	4.8	0.24	0	0	3.38	0.23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	20.20
Tue 30 Oct	0.00	4.4	4.36	0.54	2.16	2.1	2.94	0.00	0.00	0.00	0.00	1.6	9.9	8.66	1.74	1.26	2.34	0.00	0.00	0.00	0.00	0.00	0.00	0.00	42.00
Wed 31 Oct	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.74	2.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.78
October Average	0.371	0.434	0.328	0.536	0.349	0.901	1.34	1.12	0.82	0.82	0.92	0.65	0.77	0.33	0.06	0.06	0.17	0	0.02	0.2	0.12	0.52	0.88	0.12	11.846
Thu 1 Nov	0.00	0.00	0.00	0.00	0.00	1.26	2.34	3.5	9.5	3.64	1.44	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	21.68
Fri 2 Nov	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sat 3 Nov	0.00	2.46	4.24	4.06	2.94	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	13.70
Sun 4 Nov	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mon 5 Nov	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tue 6 Nov	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wed 7 Nov	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.4	0.00	0.00	0.00	0.00	1.26	4	1.74	4.8	1.6	0.00	0.00	0.00	0.00	15.80

Thu 8 Nov	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fri 9 Nov	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sat 10 Nov	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sun 11 Nov	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mon 12 Nov	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tue 13 Nov	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wed 14 Nov	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.96	2.1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.06
Thu 15 Nov	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fri 16 Nov	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sat 17 Nov	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sun 18 Nov	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mon 19 Nov	0.00	0.00	0.00	1.26	2.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.26	2.34	0.00	0.00	0.00	0.00	0.36	0.00	1.74	9.00
Tue 20 Nov	0.00	2.46	0.84	0.96	2.64	5.7	6.1	3.3	7.2	8.16	5.04	2.7	4	4.5	40.9	4.06	4.64	8	4.56	0.84	9.5	3.9	7.3	0.00	137.30
Wed 21 Nov	13.30	15.46	12.4	10.58	7.4	2.7	10.6	12.1	3.84	8.5	2.7	3.36	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	103.10
Thu 22 Nov	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.76	0.84	0.68	3.29	5.24	3.7	2.16	3.3	1.74	0.00	0.00	0.96	2.34	0.00	0.00	0.1	27.10
Fri 23 Nov	2.90	2.76	0.84	3	0.00	0.00	0.96	2.64	0	2.45	1.15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	16.70
Sat 24 Nov	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sun 25 Nov	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.96	29		1.26	2.34	0	0	0	36.60
Mon 26 Nov	3.36	0.24	4.2	4.76	0.24	0.00	0.00	0.00	0.66	2.94	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	16.40
Tue 27 Nov	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.86	1.74	0.00	0.00	0.00	0.00	0.00	2.3	14.6	7.46	6.8	3.6	0.00	0.00	0.00	38.32
Wed 28 Nov	0.00	0.00	0.00	0	2.16	1.5	3.54	2.76	0.84	0.00	0.00	0.00	0.00	3.4	2.7	2.46	1.14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	20.50
Thu 29 Nov	0.00	0.00	0.00	0.00	0.00	0.00	1.56	5.04	4.96	1.44	0.00	0.00	8.56	6.54	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	28.10
Fri 30 Nov	0.00	0.6	10.26	0.54	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.9	4.9	0.00	0.00	0.00	0.00	0.00	17.20
November Average	0.652	0.799	1.093	0.839	0.581	0.372	0.84	0.98	0.99	0.99	0.54	0.38	0.6	0.6	1.53	0.41	0.67	1.81	0.75	0.38	0.59	0.14	0.24	0.06	16.8187
Sat 1 Dec	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sun 2 Dec	3.36	3.3	0.54	0.00	0.00	0.00	2.16	1.44	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	10.80
Mon 3 Dec	1.56	2.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.60
Tue 4 Dec	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wed 5 Dec	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.36	3.3	3.8	4.27	5.54	5.84	6.1	5.76	4.8	4	5.24	1.9	0.00	0.00	0.00	0.00	0.00	50.90
Thu 6 Dec	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0	2.76	0.84	0.38	2.93	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	6.90
Fri 7 Dec	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sat 8 Dec	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.76	0.84	0.00	0.00	0.00	0.00	0	1.9	4.7	22.4	11.5	0.00	44.10
Sun 9 Dec	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mon 10 Dec	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tue 11 Dec	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wed 12 Dec	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thu 13 Dec	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fri 14 Dec	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sat 15 Dec	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0	0.66	2.94	1.2	5	4.4	5.6	2.7	0.1	22.60
Sun 16 Dec	1.30	1.56	2.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.3	0.00	5.20
Mon 17 Dec	2.76	3.3	1.14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.36	3.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	10.80
Tue 18 Dec	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0	3.36	6.94	5.04	2.64	0.66	5.04	5.14	5	0.24	0.00	0.00	0.00	34.06
Wed 19 Dec	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0	3.06	0.54	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.60
Thu 20 Dec	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fri 21 Dec	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sat 22 Dec	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	10.4	13.6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	24.00
Sun 23 Dec	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Mon 24 Dec	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tue 25 Dec	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wed 26 Dec	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thu 27 Dec	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fri 28 Dec	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sat 29 Dec	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sun 30 Dec	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mon 31 Dec	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
December Average	0.29	0.329	0.12	0	0	0	0.07	0.06	0.2	0.15	0.15	0.28	0.49	0.55	0.37	0.58	0.61	0.43	0.27	0.38	0.3	0.9	0.47	0	6.98581

Appendix F: Neural Models

1. Age:

Age

2. Gender

Gender

3. Environment

Environment

4. Infrastructure

Micro_Infrastructure