ANALYSING ROAD SAFETY IN TYNE AND WEAR

Khalid Momin

NORTHUMBRIA UNIVERSITY
Newcaastle upon tyne

1.0 Introduction

In modern-day society, cycling is crucial because it can be used for transportation and as a popular recreational activity. The value of cycling has come to the spotlight in the context of rising concerns about the sustainability of the environment, health among the public, and urban congestion. Cycling has established itself as an environmentally beneficial means of transportation as the globe struggles with the effects of climate change and the degradation of the environment (Arora et al., 2018). Individuals may actively reduce carbon footprints and encourage sustainable living by opting to cycle over driving for short distances (Neves and Brand, 2019). Congestion in densely populated regions with high densities of people has become a significant problem. Cycling offers a practical substitute for short-distance driving, lowering traffic congestion and the number of automobiles on the road (Barrett et al., 2016). The cycling environment now faces a variety of issues. Cyclists are at serious risk because of inadequate infrastructure, including junctions not planned with designated bicycle lanes (Malik, 2021). Safety issues, including collisions with automobiles and poor lighting, further exacerbate cyclists" dangers (Wood, 2020).

The dynamics of riding behaviour and its effects on safety and infrastructure can be better understood by understanding the various variables that impact cycling. Weather, geography, and urban design are environmental factors that might impact riding patterns. Cycling is convenient and practical depending on temperature, precipitation, wind, and geographic characteristics (Corcoran et al., 2014). Also, cycling participation and preferences are influenced by demographic factors. The chance that someone will choose cycling as a means of transportation can be influenced by age, gender, income, education level, and work circumstances (Heinen et al., 2013). For cyclists, safety is their top priority. Traffic volume, speed restrictions, road design, signs, order traffic signalisation, and safety features such as bike lanes, roundabouts, and traffic-calming initiatives are among the factors that impact cycling safety (Mathieson et al., 2013). Lighting conditions are also a critical variable affecting cyclists, and according to Haans and De Kort (2012), adequate lighting helps cyclists see their surroundings and enables other road users to detect and respond to them effectively. Understanding the effects of lighting on cyclists is an essential objective of this research, which considers several variables, including visibility, road layout, and lighting technology. Investigating the connection between lighting and bicycles can help us learn how to improve safety procedures, infrastructure design, and lighting options especially designed with cyclists in mind (Forsyth and Krizek, 2011).

Several studies have examined the connection between riding and lighting conditions, particularly emphasising how lighting affects rider visibility and safety. The results of these studies offer data-driven findings and perceptions regarding the impacts of lighting innovations, road lighting layouts, and psychological aspects on cyclists. According to Shaw (2016), adequate lighting substantially improved cycle visibility, lowering the risk of collisions and near-miss events. To improve safety, the research suggested installing enough lighting along cycling paths. Increased light levels have been positively correlated with fewer accidents involving cyclists (Reynolds et al., 2009). Using accident records and observational data, Sawyer and Kaup (2014) examined the safety results of riding in well-lit versus low-lit environments. Results showed that low-light situations had a greater incidence of incidents involving cyclists compared to daytime circumstances. The study suggested implementing upgraded lighting infrastructure and raising cyclist and motorist awareness during low-light conditions. Also, studies have demonstrated that cyclists'' behaviour, including speed and lane location, differed based on how they perceived the lighting conditions, highlighting the need to consider cyclists'' sensory experience to ensure their safety (Xie and Spinney, 2018). Dey et al. (2022) used surveys and interviews to investigate how bicycles, drivers, and pedestrians perceived the lighting situation.

The findings indicated that cyclists viewed lighting differently from other road users, highlighting the need for specialised lighting solutions to meet their unique visual needs. Pietrantonio (2021) examined how cyclists perceived themselves in various lighting circumstances when using dynamic lighting systems. Compared to static lighting solutions, the research showed that dynamic lighting considerably improved cyclists'' ' safety and visibility. Dynamic lighting alters intensity and patterns depending on environmental parameters (Hamm and Hinterwaelder, 2020). A study conducted in London analysed the pedalling speeds, itineraries, and trip durations of approximately 1,000 cyclists over a year (Aldred et al., 2018). The researchers used data from GPS-enabled cycle computers to examine how illumination affects bikers. According to the research, bicycle speeds were higher on streets with adequate light than on those with inadequate lighting. The study also found a link between well-lit routes and the existence of lighting systems and a general rise in the number of bicycle journeys.

Poor illumination is frequently considered to cause bicycle accidents and adversely influence riders'' safety, although several studies contend that this relationship is either insufficient or nonexistent (Njå and Nesvåg, 2007). Chen et al. (2017) suggest that less illumination would not always increase accidents in some situations, such as places with lower traffic levels or dedicated bike pathways. During low-light circumstances, bicycle accidents significantly decreased, according to case-control research by Prati et al. (2018), which they attributed to slower driving speeds and higher rider caution. Ahmed et al. (2022) investigated the relationship between lighting levels and cycling accidents using a naturalistic cycling study, revealing a lower accident rate in low lighting conditions, possibly due to increased cyclist alertness. The disparate results in the research under evaluation reflect the nuanced nature of the connection between poor illumination and bike accidents.

The specific results are presumably a result of several elements, including the particular setting, environmental circumstances, road infrastructure, and cycling behaviour. In places with a small amount of traffic or defined bike lanes, for instance, low illumination levels may be more advantageous since they encourage cyclist caution and slow down drivers (Qasem, 2020). However, cyclists" safety may be jeopardised by poor lighting in congested metropolitan areas or at complicated crossings (Khattak et al., 2021). The literature analysis indicates various viewpoints on the connection between poor lighting and bike accidents. According to some studies, low light levels have been linked to fewer bicycle accidents; however, other research disputes this idea. The results highlight the significance of considering several variables, including the particular context and environmental circumstances, when evaluating the effect of lighting on cycling safety. Future studies should concentrate on determining the ideal light exposure settings for various riding locations and creating focused interventions to improve biker safety.

1.1 Aim

Cycling plays a crucial role in sustainable transportation systems, offering an eco-friendly mode of commuting. In light of this, this research investigates the utilisation patterns of bicycles in Tyne and Wear, considering different variables such as lighting conditions, environmental factors, and traffic flow dynamics.

1.2 Objectives

- Conduct an extensive literature review examining the key factors that significantly impact bicyclists across various aspects of their environment.

- Acquire access to relevant data sources and analyse their implications for bicyclists, considering how they affect their safety and overall experience.
- Formulate statistical foundations for the chosen research topic and develop mathematical frameworks and approaches to analyse and interpret the data effectively.
- Identify and evaluate the variables influencing cyclists" infrastructure utilisation while ensuring safety.
- Assess the study's limitations and propose recommendations for enhancing rider safety through further investigations and research.

2.0 Study Area

The study area for this research is Tyne and Wear, which has five boroughs:

1) Newcastle Upon Tyne
2) North Tyneside
3) South Tyneside
4) Gateshead
5) Sunderland

The figure below shows the five boroughs of Tyne and Wear:

Figure 1 Study Area Tyne and Wear

Tyne and Wear has seen a significant increase in cycling in recent years. Data from the Department of Transport (2019) show that between 2010 and 2019, there was a significant 63% rise in the number of bicycles in the area. Local councils have found themselves obligated to respond proactively to support and promote cycling as an environmentally friendly way of transport of this spike in bicycle activity.

The authorities in Tyne have given the construction of bike infrastructure top priority and Wear to encourage riding. In addition to building accessible bike parking facilities, authorities have developed a comprehensive network of cycling pathways across the area (Yeboah and Alvanides, 2015). By making bicycle routes safer and easier to access, these infrastructure upgrades hope to persuade more people to choose riding as their primary means of transportation. These cycling projects provide advantages that go beyond simple practicality. The potential health benefits of Tyne andWear's enhanced bicycle infrastructure were noted in a 2016 Newcastle University research, and according to the study's findings, cycling on designated lanes and trails can help lower the risk of cardiovascular disease and improve psychological well-being (Tainio et al., 2016). These results highlight the value of funding bike infrastructure to improve people's health and well-being.

The locals" perspectives on Tyne and Wear show the support for bike infrastructure. The city council reports that 68% of locals in the area support the development of additional specifically designated cycleways (Transport, 2020). This encouraging response from the neighbourhood highlights the importance of maintaining investment in bicycle infrastructure to satisfy the rising demand and provide a fun and safe cycling experience for everybody. The Quayside is one place where bike activity has dramatically increased. Cycling activity in this region increased by an astounding 260% between 2010 and 2016, demonstrating the benefits of the upgrades to the cycling infrastructure (Yeboah and Alvanides, 2015). This demonstrates how effectively cyclists may be attracted to and accommodated on well-planned and accessible bicycle routes.

As a result of the localgovernment's efforts to provide bike infrastructure, cycling has seen a substantial increase in Tyne and Wear in recent years. Cycling has become more convenient due to the improvements in bike lanes and parking facilities, which have also improved locals" health and sense of well-being. Cycling infrastructure will continue to be essential in advancing sustainable mobility and making cycling in Tyne and Wear safer and more pleasant with thecommunity's strong support.

3.0 Methodology

The research study includes a framework for a methodology that combines data-driven learning and mathematical approaches to ensure a thorough assessment of cycling safety. Crash safety models are a crucial instrument used to evaluate rider safety properly (Yasmin and Eluru, 2016). To discover risk variables linked to bicycle crashes, a standard strategy involves the study of crash records using mathematical approaches, including logistic regression (Peng et al., 2012). These models may calculate the probability of a bicycle crash by considering several variables, such as the current weather, the amount of traffic, the design of the roads, and other pertinent elements (Theofilatos et al., 2012).

In order To evaluate the safety of bicycle infrastructure, simulation models are used in addition to accident safety models. These models use mathematical techniques to simulate how bikers and cars behave on the road (Twaddle et al., 2014). Cycling pathways and roundabouts are two examples of planned bicycle-friendly infrastructure that may have their safety assessed before being built by using simulation models. Additionally, it is possible to evaluate the efficacy of several safety actions, including those for reducing speed and traffic congestion (Rinke et al., 2017). The safety of various bicycle infrastructure designs, such as road junctions and designated riding lanes, is crucially assessed using these models. These models may be used in the planning stage of a project to evaluate possible hazards and the efficiency of different safety precautions (Nan et al., 2020). By doing so, it is possible to make well-informed choices and ensure the safety of cyclists is given priority when designing the infrastructure for riding.

The study utilises various data sources to obtain comprehensive information for analysis. These data sources include:

1) Traffic and Data Unit (TADU): This source provides data on traffic patterns, including vehicle counts, speeds, and other relevant traffic-related information.
2) Traffic Flow Database System (TRADS): TRADS offers a database of traffic flow data, including information on vehicle movements, traffic volumes, and congestion levels.

3) Meteorological Data: Meteorological data sources supply information on weather conditions, including temperature, precipitation, wind speed, and visibility. These data are crucial in understanding the impact of weather on cycling behaviour and safety.
4) National Travel Survey (NTS): The NTS is a comprehensive survey conducted at the national level, providing valuable insights into travel behaviour, including cycling habits, travel distances, and purposes.
5) Office of National Statistics (ONS): ONS offers a wide range of socio-economic data that can be used to analyse factors such as population demographics, income levels, and employment patterns, which may influence cycling behaviour.
6) Urban Observatory Newcastle (UON): The UON is a local data repository that collects various urban data, including transportation data, infrastructure information, and social indicators.

The crash data utilised in this study is obtained from The Traffic and Data Unit (TADU) through the Captia Innovation Road Traffic Accident System. This system grants access to the UK STATS 19 police database, specifically the section related to bicycle fatalities (CIRTAS). The database includes Tyne and Wear County accident data dating back to 1998. However, only data dating from 2005 to 2018 is considered for modelling purposes. The Gateshead Council, which oversees statistical data management for the northeastern part of England, has set out criteria consistent with this period. Due to almost certain significant changes in infrastructural and traffic-related circumstances that perhaps happened after 2005, it was decided to focus on data beginning in that year. As a result, this study's analysis and modelling use data acquired after 2005 to assure relevance and accuracy.

The summary of the analysis and its data sources are shown in the table below.

1. ***Traffic Flow***

Table 1 Traffic Flow

Traffic-Flow Variation	Source of Data	Analysis Performed
Monthly	Traffic-flow Database System	a. Polynomial regression b. Flow rate
Hourly	Traffic-flow Database System	a. Polynomial regression b. Flow rate
Daily	Traffic-flow Database System	a. Flow b. Flow rate

2. *Lighting Conditions*

Table 2 Lighting Conditions

	Source of Data	Analysis Performed
Monthly	UON(Urban Observatory Newcastle)	a. Polynomial regression b. 24-hour lighting average
Flow	UON(Urban Observatory Newcastle)	a. Polynomial regression b. Flow and Flow rate

3. *Meteorological Conditions*

Table 3 Meteorological Conditions

	Source of Data	Analysis Performed
Monthly	UON(Urban Observatory Newcastle)	Average Rainfall (mm)

4. Gender Data

Table 4 Gender Data

	Source of Data	Analysis Performed
Male and female	National Travel Survey	a. Trip-per-person b. Trip rate c. Male/Female ratio

5. Crash Data

Table 5 Crash Data

Crashes	Source of Data	Analysis Performed
Crash Variables	Traffic and Data Unit	a. Frequency b. Crash Rate

3.1 Crash Dataset

A total of 2056 reported accidents were recorded between 2005 and 2018 in the Traffic and Flow Unit Database (TADU). Among these crashes, 79.4% were considered minor events, making up the majority. Only 0.7% of the accidents resulted in fatalities, making up a comparatively tiny part of the total. In the database, severe injuries suffered by cyclists comprised the remaining recorded instances (19.9%).

Table 6 Collision Severity

Collision Severity	**Flow (F)**	**Crash Rate (Cr)**
Fatal	14	0.7
Serious	410	19.9
Slight	1632	79.4
Total	2056	100.0

1. *Junction Location*

The 20-meter radius at a junction has the highest collision rate (31%), followed by the mid-junction zone (on a roundabout or the main road), with a crash rate of 28.5%. Only one collision occurs while coming from a slip lane, and only four crashes occur when leaving a roundabout. By analysing crash statistics at different junction sites, authorities may identify junctions that need to be improved to reduce the frequency of crashes and boost road safety (Giles-Corti et al., 2020).

Table 7 Junction Location

S.no	Junction Location	Number of crashes	Crash Rate
1	Approaching the junction or waiting/parked at the junction exit	349	17.0
2	Cleared junction or waiting/parked at junction exit	112	5.4
3	Entering from the slip road	1	.0
4	Entering the main road	296	14.4
5	Entering roundabout	29	1.4
6	Leaving the main road	41	2.0
7	Leaving roundabout	4	.2
8	Mid junction - on a roundabout or main road	586	28.5
9	Not at or within 20 metres of the junction	638	31.0
	Total	2056	100.0

2. *Junction Control*

The table reveals intriguing findings regarding the crash rates at different junctions. Junctions without controls and giveaways had the highest frequency of crashes, accounting for a staggering 62.1% and 31.1%, respectively. In contrast, signal-controlled junctions demonstrated a shallow crash rate of just 6.5%. This highlights the significant impact that traffic signals have in reducing crashes. These results suggest that implementing regulated traffic signals at give way or uncontrolled junctions could effectively decrease the crash rate. However, it is essential to consider the potential consequences of such a measure. Introducing additional traffic signals may result in a decline in traffic flow, potentially affecting driver behaviour and overall road dynamics (Nguyen et al., 2018). Interestingly, the data reveals that only 0.3% of crashes were recorded at intersections with stop signs. This suggests that the presence of stop signs alone may not be as effective in preventing accidents as signal-controlled junctions (Pandian et al., 2009).

Table 8 Junction Control

S.No	**Control type**	**Number of crashes**	**Crash Rate**
1	Automatic traffic signal	134	6.5
2	Give way or uncontrolled	1276	62.1
3	No Control	639	31.1
4	Stop sign	7	.3
	Total	2056	100.0

3. *Junction Detail*

T Junctions or Staggered Junctions exhibit the highest crash rate among all junction details, with a rate of 44.6%. These junctions are more prone to collisions due to merging roads, lane switching, limited visibility of oncoming traffic, and potential speeding or failure to stop (Pai, 2009). Additionally, the crash rate within 20 meters of a junction is significantly higher than other junction details, standing at 31%. Focusing on reducing the crash frequency at these particular junctions is crucial. Crossroads and roundabouts account for most crashes at 9.5% and 9.1%, respectively. Slip roads, however, record the lowest number of crashes, with only 14 reported incidents.

Table 9 Junction Detail

S.No	Junction Detail	Number of crashes	Crash rate
1	Crossroads	196	9.5
2	Mini roundabout	12	.6
3	Multiple Junction	3	.1
4	Not at or within 20 metres of the junction	638	31.0
5	Other junction	28	1.4
6	Roundabout	188	9.1
7	Slip Road	14	.7
8	T or staggered junction	917	44.6
9	Using a private drive or entrance	60	2.9
	Total	2056	100.0

4. *Vehicle Manoeuvre*

Proceeding straight ahead emerges as the primary manoeuvre associated with crashes, with a high crash rate of 80.9%. In contrast, all other manoeuvres exhibit significantly lower crash rates. These accidents often occur due to impatient drivers who accelerate and attempt to overtake cyclists (Stone and Broughton, 2003). Switching lanes while cycling is relatively safer compared to lane changes involving motor vehicles, which show a slightly higher crash rate.

Table 10 Vehicle Manoeuvre

S.No	Manoeuvre	Frequency	Crash Rate
1	Changing lanes to the right/left	25	1.2
2	Going ahead, left-hand bend	21	1.0
3	Going ahead other	1664	80.9
4	Going ahead, right-hand bend	34	1.7
5	Moving off	25	1.2
6	Overtaking moving vehicle on its offside	14	.7
7	Overtaking on nearside	22	1.1
8	Overtaking a stationary vehicle on its offside stationary vehicle	25	1.2
9	Parked	1	.0
10	Reversing	4	.2
11	Slowing or stopping	20	1.0
12	Turning left	46	2.2
13	Turning right	142	6.9
14	U	1	.0
15	U Turn	4	.2
16	Waiting to go ahead but was held up	3	.1
17	Waiting to turn left	1	.0
18	Waiting to turn right	4	.2
	Total	2056	100.0

5. *Speed Limit*

Cycling accidents are more likely to occur on urban roads where the speed limit is set at 30 mph (Isaksson-Hellman and Töreki, 2019). High traffic volume on these roads contributes to the elevated crash rate of 82.1%. In comparison, the crash rates on dual carriageways with a speed limit of 60 mph and roads with a speed limit of 40 mph are significantly lower, standing at 7.4% and 5%, respectively. It is worth noting that the absence of dedicated bike lanes on these types of roads may be a contributing factor, as bike lanes are predominantly found on roads with a 30 mph speed limit (Siddiqui et al., 2012).

Table 11 Speed Limit

S.No	**Speed Limit(mph)**	**Frequency**	**Crash rate**
1	20	60	2.9
2	30	1687	82.1
3	40	102	5.0
4	50	26	1.3
5	60	153	7.4
6	70	28	1.4
	Total	2056	100.0

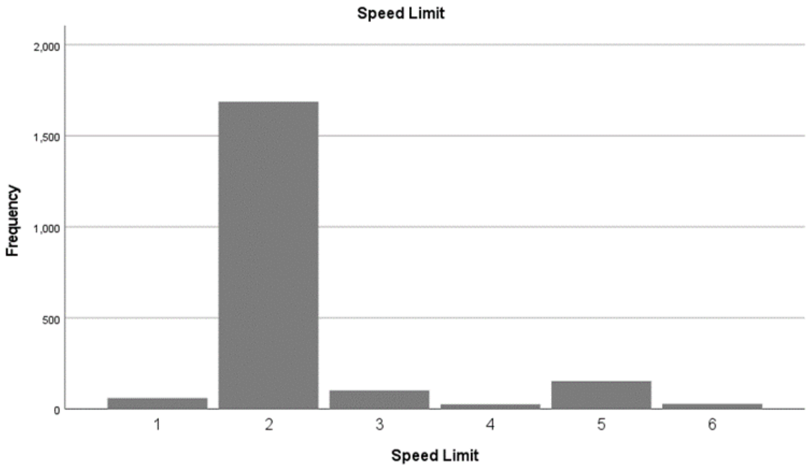

Figure 2 Speed Limit

6. *Casualty Gender*

The crash rate for male cyclists is considerably higher, with a total of 1813 reported crashes, while females account for only 11.8% of the crashes. This disparity in crash rates can be attributed to several factors. First, compared to their female counterparts, men bikers often go farther and ride more frequently. The likelihood of being in an accident naturally increases with more exposure to riding (Damsere-Derry et al., 2017). Men take more significant risks while cycling than women, which has also been noticed when examining cycling behaviours (Garrard et al., 2008). This might entail behaviours that increase the risk of getting in a collision, such as driving more quickly, making risky manoeuvres, or disobeying traffic laws (Aldred et al., 2016).

Notably, these results do not indicate that all male bikers engage in unsafe behaviour or that female riders are impervious to collisions. Instead, they draw attention to trends that have been noticed more generally. Knowing these gender-related disparities in crash rates might help guide specifically designed measures and awareness campaigns to encourage safer riding practices for everyone, regardless of gender.

Table 12 Casualty Gender

Gender	Frequency	Crash rate
Female	243	11.8
Male	1813	88.2
Total	2056	100.0

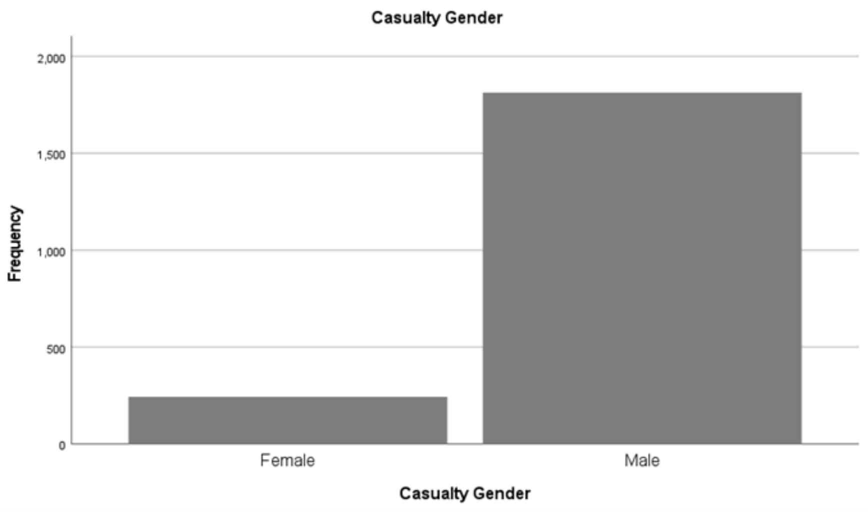

Figure 3 Casualty Gender

7. *Weekday or Weekend*

Higher traffic volumes during peak hours on weekdays contribute to an increased risk of collisions, resulting in 76.6% of crashes being recorded on weekdays. 23.6% of all accident occurrences happen on the weekends. On weekdays, many people cycle to work or school, subjecting them to rush-hour traffic and increasing collision rates (Kotresh, 2013). According to Keay and Simmonds (2005), the focused weekday activity and the interaction between bicycles and heavy traffic during these peak hours contribute to the more significant percentage of accidents documented on weekdays.

Table 13 Weekday or Weekend

Day	Frequency	Valid Percent
Weekday	1575	76.6
Weekend	481	23.4
Total	2056	100.0

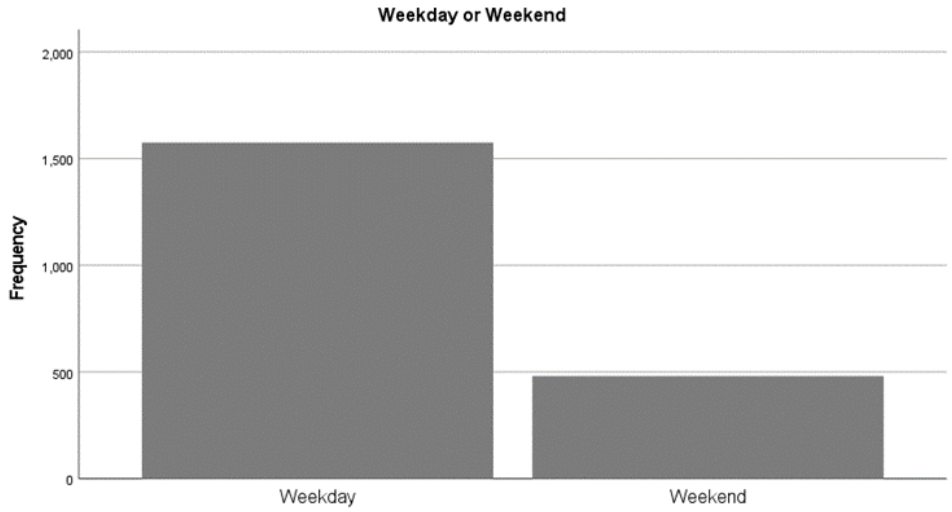

Figure 4 Weekday or Weekend

8. *Daily Variation*

The crash rates on weekdays and weekends differ from those on weekends, with weekday rates being substantially higher. One reason for this discrepancy is the effect of time pressure on commuters, which may result in an increased desire to take risks and participate in dangerous behaviour while on the road (Au, 2020). Weekday commuters are under pressure to get to work on time, which may affect how they make decisions and raise the collision rate during these times (Cœugnet et al., 2013).

Table 14 DailyVariation

Day	Frequency	Crash rate
Monday	303	14.7
Tuesday	287	14
Wednesday	339	16.5
Thursday	333	16.2
Friday	313	15.2
Saturday	262	12.7
Sunday	219	10.7

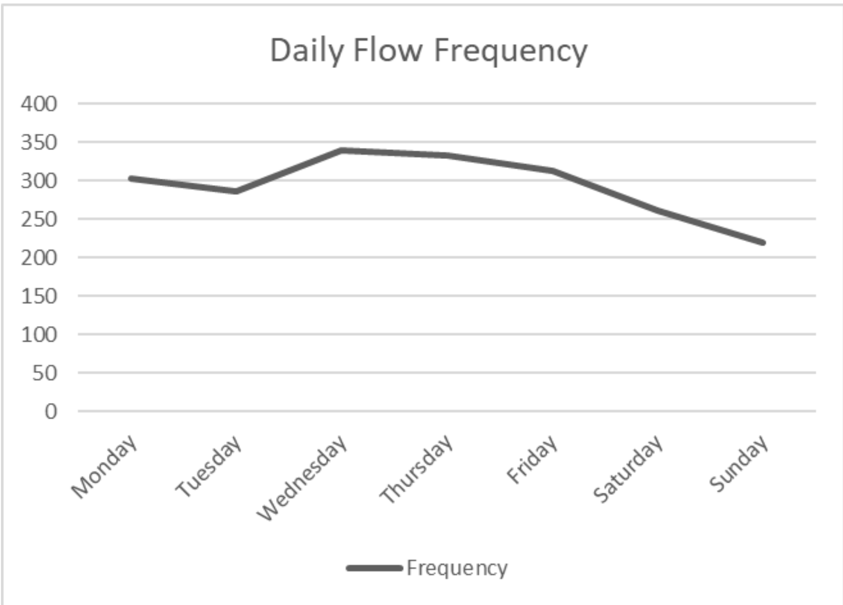

Figure 5 Daily Variation

9. *Weather Conditions*

As a result of drivers being more careful than they would be in clear weather, crash rates tend to be lower in bad weather (Hao and Daniel, 2016). Slower cycling speeds in bad weather, when riders prioritise avoiding hazards and obeying traffic laws, are one element that contributes to this tendency (McClintock and Cleary, 1996). Part-time cyclists are also more likely to choose other transportation modes or stay home in inclement weather, lowering the risk of accidents. In bad weather, such as high winds, rain, or snow, bicycle speeds are substantially slower, encouraging more cautious riding and decreasing collision rates (Yang et al., 2021). Recognising that bad weather can still cause accidents is crucial since it reduces visibility and makes the roads slick. The interplay between weather and crash rates is complicated and diverse since it depends on several factors.

Table 15 Weather Conditions

Weather	Frequency	Crash rate
Good	1904	92.5
Bad	152	7.5
Total	2056	100.0

Figure 6 Weather Conditions

10. Light Conditions

Cycling at peak and commute times in the daylight, during which more cars are on the road, is mostly to blame for the high collision rate of 83.09%. In contrast, due to variables such as lack of street lighting or dimly lit streets, the collision rate decreases throughout the night to 16.91%. According to Lubitow et al. (2019), full-time cyclists are likelier to ride in the dark than part-time cyclists who favour daytime riding. This is explained by the increased caution and awareness of full-time cyclists riding at night (Lubitow, 2017). Because visibility is often higher during the day, drivers tend to feel more confident on the road. It might result in increased speeding, which raises the chance of accidents (Aldred and Woodcock, 2015).

It should be emphasised that the reduced collision rate seen at night time is likely a result of the presence of streetlights on the streets and the conscientious riding habits of full-time cyclists (Balsas, 2003).

Table 16 Lighting Conditions

Lighting	Frequency	Crash rate
Daylight	1709	83.09
Darkness	347	16.91

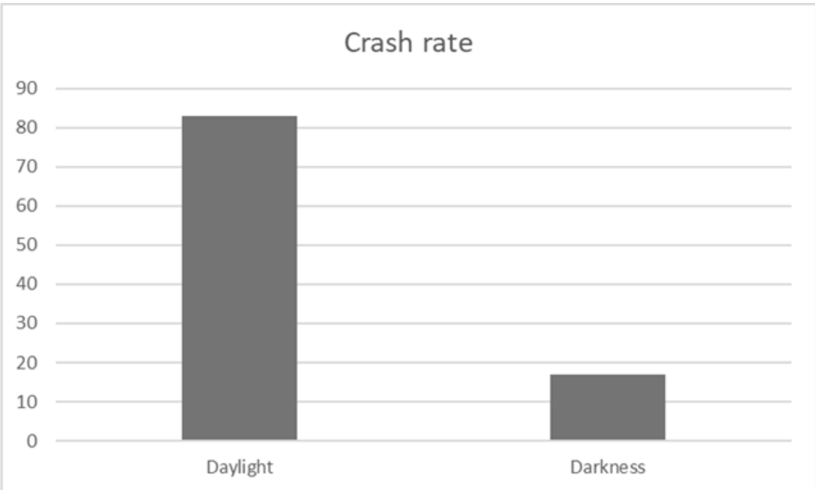

Figure 7 Lighting Conditions

11. *Road Surface Conditions*

Dry weather can make driving seem safer to drivers, encouraging them to take more significant risks and drive faster, which raises the collision rate. On the other hand, unfavourable weather conditions, including frigid temperatures, snowy conditions, and slippery roads, frequently lead to a reduced collision rate (Kilpeläinen and Summala, 2007). This can be explained by the fact that full-time cyclists are more inclined to ride during inclement weather (Perrels et al., 2015). A higher crash rate of 82.6% is observed when the road surface is dry, a rate that is much higher than the crash rate noted when the road surface is unfavourable. However, it is crucial to remember that foul weather presents new obstacles and possible dangers for both motorists and bikers, which can help minimise the collision rate in such situations (Böcker et al., 2013).

Table 17 Road Surface Conditions

Surface Conditions	Frequency	Crash Rate
Dry	1699	82.6
Frost	11	.5
Snow	3	.1
Wet/Damp	343	16.7
Total	2056	100.0

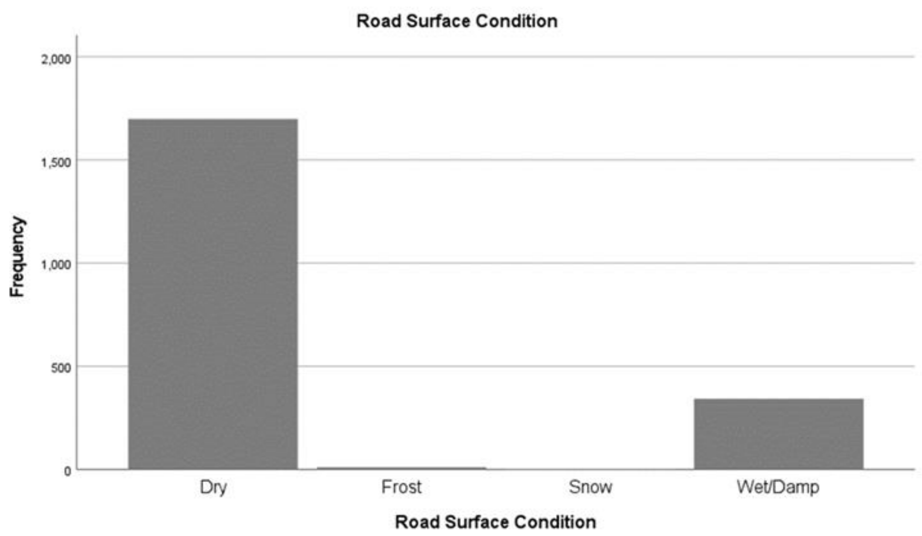

Figure 8 Road Surface Conditions

12. *Journey Purpose*

The overwhelming number of crashes reported in this dataset were classified as ""unknown"" or ""other"" regarding thetrip's intended purpose, suggesting recreational or occasional riding by part-time cyclists. People pedalling to or from work have a crash rate of 9.3%, while people pedalling to or from school face a collision rate of 4.4%. According to these results, full-time cyclists are less likely to be involved in collisions than part-time cyclists (Johnson et al., 2009). This could be due to things such as their confident driving manner, compliance with correct security gear usage, and improved understanding of road conditions. Cycling regularly shows better expertise and knowledge, which helps full-time cyclists manage the road more cautiously and reduce possible dangers (Muir et al., 2010).

Table 18 Journey Purpose

S.No	Purpose	Frequency	Crash rate
1	Commuting to/from work	192	9.3
2	Journey as part of work	84	4.1
3	Not known	423	20.6
4	Other (Leisure and Entertainment)	1262	61.4
5	Pupil riding to/from school	91	4.4
6	Taking pupils to/from school	4	.2
	Total	2056	100.0

13. *Monthly Variation*

An annual pattern can be seen in the crash rate data, with an increasing tendency beginning in January and peaking at 13.5% in July. The crash rate after that steadily declines in the second half of the year. There are several causes behind this pattern. First, winter months observe lower collisions since full-time bikers are more inclined to ride during that time. As summer draws near, there are more bikers overall, including part-time riders, which causes both the collision rate and the number of recorded occurrences to climb (Chalmers, 2013). In addition, the summer months often see an increase in traffic because of the growth in leisure and vacation-related activities. A minor increase in the crash rate during this period may result from the higher congestion levels. On the other hand, January has the highest crash rate, at 4.7%, while December has the lowest, at 3.2%.

The seasonal fluctuations in accident rates remind of the year-round effects of variables, including weather, riding habits, and general traffic congestion (Koetse and Rietveld, 2009).

Table 19 Monthly Variation

Month	**Frequency**	**Crash Rate**
January	97	4.7
February	121	5.9
March	141	6.9
April	169	8.2
May	183	8.9
June	231	11.2
July	278	13.5
August	236	11.5
September	245	11.9
October	164	8
November	126	6.1
December	65	3.2
Total	2056	100.0

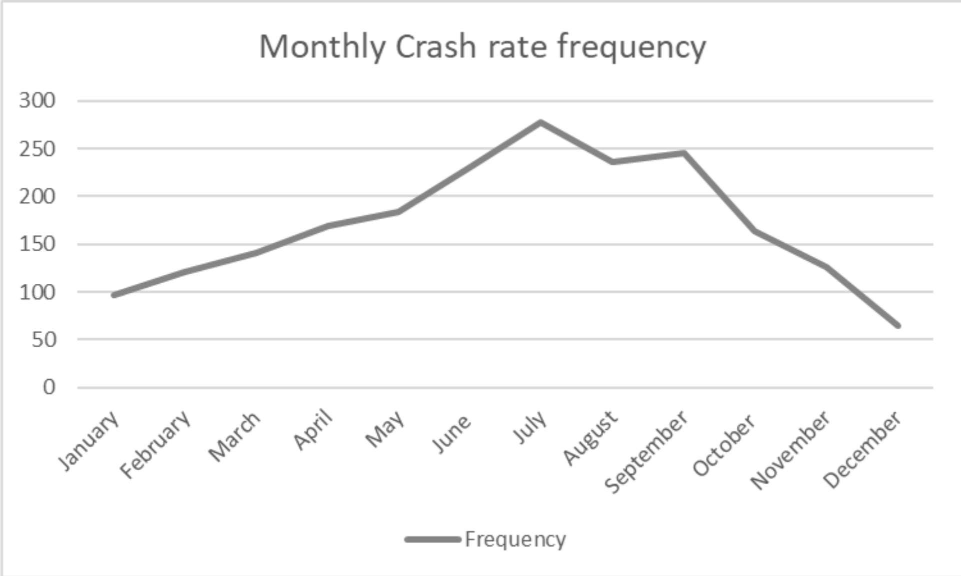

Figure 9 Monthly Crash Frequency

14. Hourly Variation

Six hundred fifty-eight collisions occurred between 3 PM and 6 PM, constituting 32% of all recorded events. At 5 PM, when collisions peaked, 251 incidents—or 12.2% of all collisions—were reported, the most significant amount observed. Three hundred thirty-six collisions, or 16.3% of the total, occurred between 9 AM and 12 PM, closely trailing the overall total. The fewest incidents, however, occurred between one and six in the morning, when there were just 41 accidents or 2% of all accidents. In particular, there were only six reported crashes between the hours of 2 and 3 in the morning.

The statistics show a distinctive trend towards higher crash prevalence throughout high-traffic hours, with the least number of crashes unfolding during off-peak periods. These results highlight how collision risk is affected by busy traffic conditions.

Table 20 Hourly Crash Rate

Hour	Frequency	Crash Rate
0	14	.7
1	4	.2
2	2	.1
3	5	.2
4	4	.2
5	12	.6
6	25	1.2
7	78	3.8
8	161	7.8
9	62	3.0
10	67	3.3
11	107	5.2
12	113	5.5
13	118	5.7
14	122	5.9
15	181	8.8
16	226	11.0
17	251	12.2
18	177	8.6
19	130	6.3
20	78	3.8

21	**55**	**2.7**
22	45	2.2
23	19	.9
Total	2056	100.0

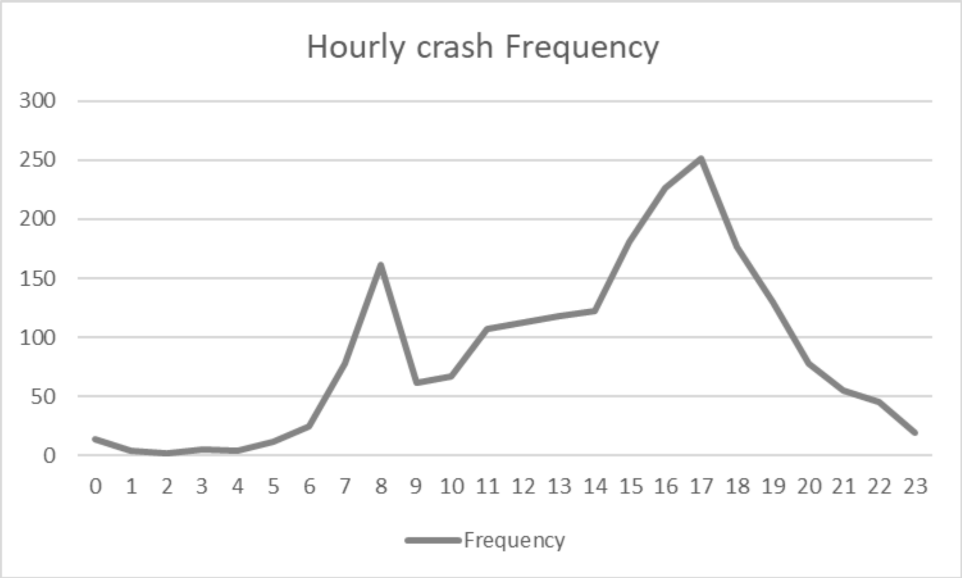

Figure 10 Hourly Crash Frequency

3.2 Flow Data

This section investigates how changes in rider usage on an hourly, daily, and monthly basis affect cycling flow in response to changing lighting conditions, weather, and other factors.

1. *Monthly Traffic Flow Variations*

According to the data, there was a noticeable rise in traffic flow throughout the summer, withJune's flow rate hitting 12.4% andJuly's reaching 12.5%. The peak travel season and several holidays that fall around this period might be blamed for the increase in traffic (Yeoman, 2009). On the other hand, throughout the winter, the flow rate decreases, with December having a flow rate that is the lowest at 4%. Unfavourable weather in certain areas may contribute to less travel throughout the winter months (Keay and Simmonds, 2005).

The flow rate keeps increasing steadily from January and continues to do so until it hits the highest point in the peak summer months of June and July. The flow rate then starts to decline steadily after that. These results indicate a clear seasonal trend in traffic movement, with high flow in summer and lower wintertime flow rates.

Table 21Monthly Flow

Month	Flow	Flow Rate
January	148555	4.4
February	207098	5.8
March	252427	7.1
April	241248	6.7
May	317704	8.9
June	444326	12.4
July	445727	12.5
August	391025	10.9
September	366170	10.2
October	358555	10
November	249949	7
December	143601	4
Total	3574826	100

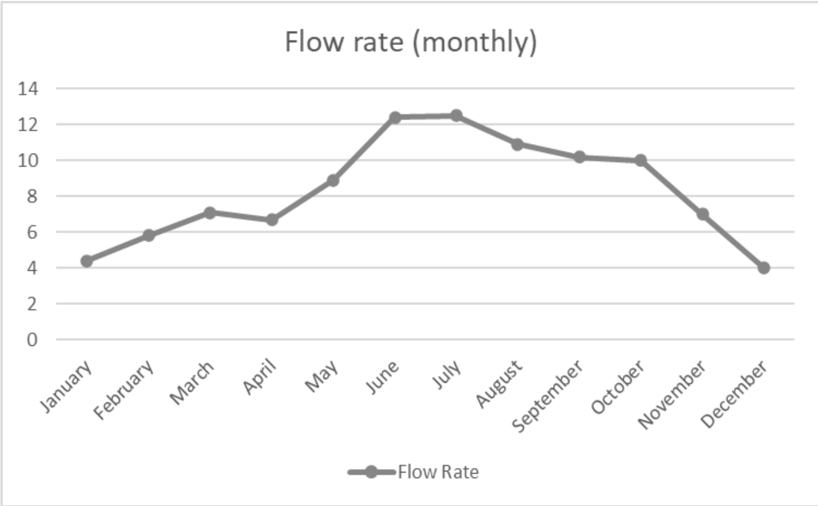

Figure 11 Monthly Flow

2. *Hourly Traffic Flow Variation*

The morning and evening rush hours generally go from 7 AM to 10 AM and 4 PM to 7 PM are when the most considerable flow rates are recorded. Many people commute during these peak hours to and from work, which causes more traffic congestion (Ewing et al., 2018). A subsequent increase in flow rate arises between 12 PM and 2 PM, most likely due to people departing for lunch or performing activities during their break hours. The lowest flow rates, on the other hand, are seen in the early morning hours of 1 AM to 5 AM and in the late night hours of 10 PM to 1 AM. Because most people are sleeping at these times, there is less traffic on the roads. Fewer cars are on the road, and less traffic during these off-peak hours (Downs, 2005).

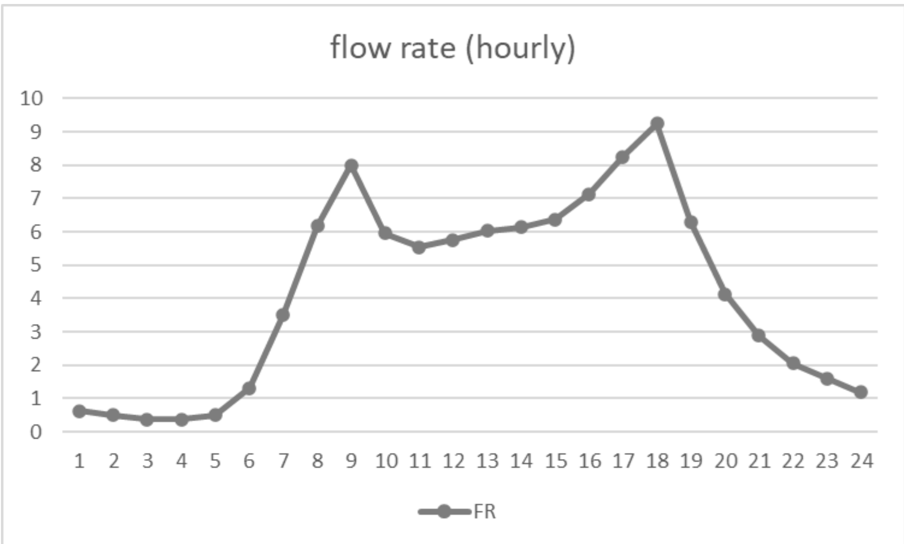

Figure 12 Hourly flow

Table 22 Hourly Flow Variation

Hour	Frequency	Flow rate
1	22128	0.62
2	18090	0.51
3	13376	0.37
4	13219	0.37
5	17935	0.5
6	46914	1.31
7	125878	3.52
8	221054	6.18
9	285898	8
10	213058	5.96
11	198577	5.55
12	205888	5.76
13	215531	6.03
14	219224	6.13
15	228030	6.38
16	254738	7.13
17	295327	8.26
18	330432	9.24
19	225189	6.3
20	147682	4.13
21	103008	2.88
22	73809	2.06
23	57140	1.6
24	42701	1.19

3. *Daily Traffic Flow Variation*

The data in the table demonstrates a steady flow rate decline from weekdays to weekends. On Monday, Tuesday, Wednesday, and Thursday, exceptionally high flow rates are apparent, suggesting typical peak traffic. Flow rates start declining as the week goes on on Fridays, and Saturdays and Sundays observe the lowest flow rates. Several factors may be responsible for the decrease in flow rates during weekends. Since many people take the weekends off from jobs or school, commute distances are reduced or even eliminated (Downs, 2005).

According to Pooley et al. (2013), most individuals do not commute as far on the weekends since they often take the day off from their job or school. Additionally, many individuals could stay home over the weekends, lessening traffic on local roads (Lucas, 2006).

Table 23 Daily Flow Variation

Day	Frequency	Flow rate
Monday	564244	15.8
Tuesday	587629	16.4
Wednesday	579442	16.2
Thursday	565721	15.8
Friday	536798	15
Saturday	371120	10.4
Sunday	369872	10.3

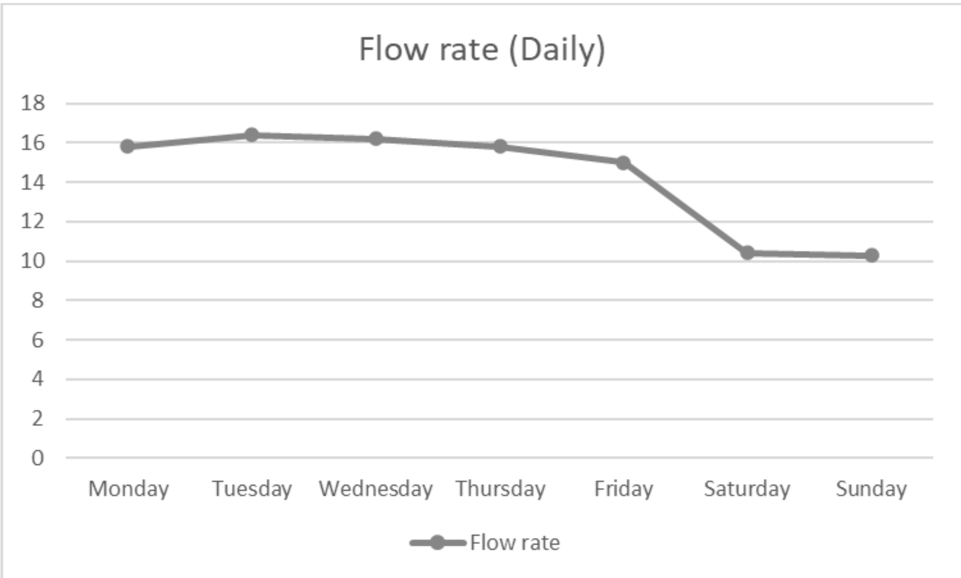

Figure 13 Daily Flow Rate

4. *Monthly Lighting Variation*

The table represents the yearly variance in daylight hours, with June having the longest days and December having the shortest days. The duration of daylight is a crucial factor to consider when selecting a transportation mode (Heinen et al., 2010). Cycling is far more inclined to encounter a higher flow rate in the summer when there are considerably more daylight hours (Dill and McNeil, 2013). In contrast, cycling may decrease the flow rate in the winter when the number of daylight hours is reduced (Pucher, 2001).

Table 24 Monthly Flow Variation

Month	Daylight (Hour)
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

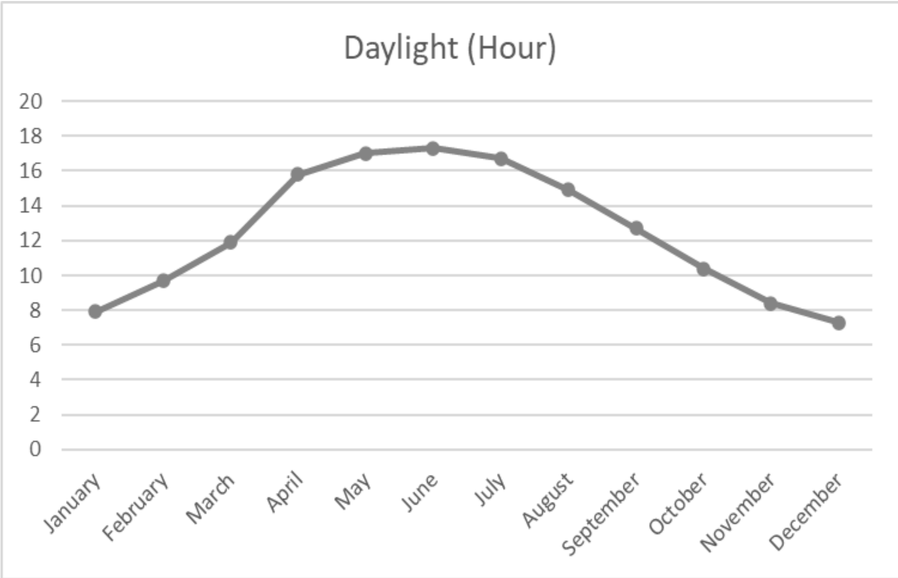

Figure 14 Monthly Lighting Variation

The flow was substantially higher during the day than at night, as seen in the table below, where 81.47% occurred throughout the day versus 18.53% at night.

Table 25 Flow Rate in Daylight/Darkness

Lighting condition	Flow	Flow Rate
Daylight	2912237	**81.47**
Darkness	662589	**18.53**
Total	**3574826**	**100.00**

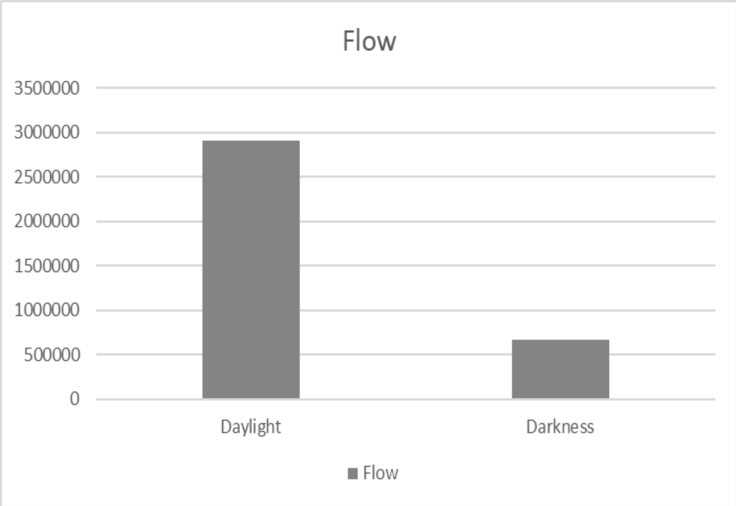

Figure 15 Flow Rate in Daylight/Darkness

5. *Monthly Meteorological Variation*

Based on the data, March and April receive the highest rainfall, with 954.9 mm and 1089.8 mm, respectively. This finding is consistent with springtime, frequently characterised by increasing precipitation. On the contrary, May had the smallest percentage of precipitation, totalling 108.6 mm. The summer season generally starts in May, and compared to other seasons, it is often drier (Hänsel et al., 2019). Beginning in August, precipitation progressively increases before beginning to decline until December.

Table 26 Monthly Precipitation

Month	Precipitation (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

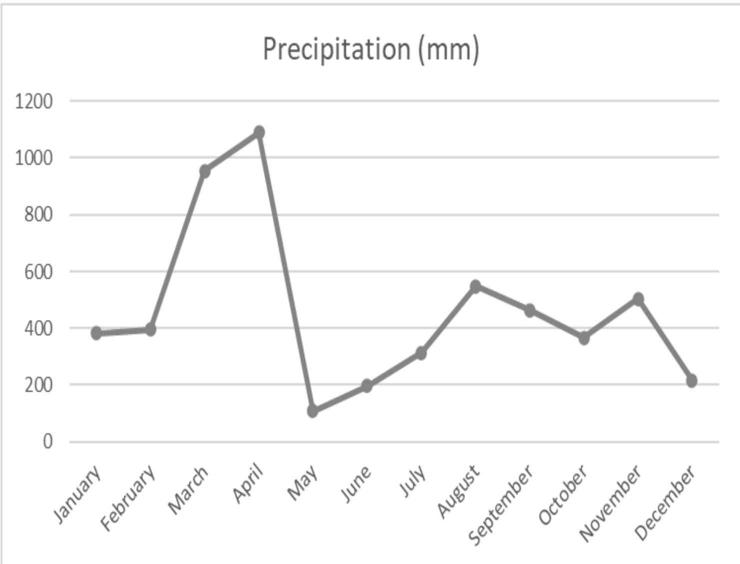

Figure 16 Monthly Precipitation

The flow rate in good and bad weather conditions is calculated in the table below:

Table 27 Meteorological Flow Rate

Meteorological Conditions	**Flow Rate**
Good	78.26
Bad	21.74

6. *Gender Flow Rate*

According to the data, males account for a flow rate of 77.4%, while females have a flow rate of 22.6%. This indicates that a more significant proportion of cyclists in the dataset are male, while females comprise a smaller percentage. The table provided shows the flow rate based on gender.

Table 28 Gender Flow Rate

Gender	**Flow Rate**
Male	77.4
Female	22.6

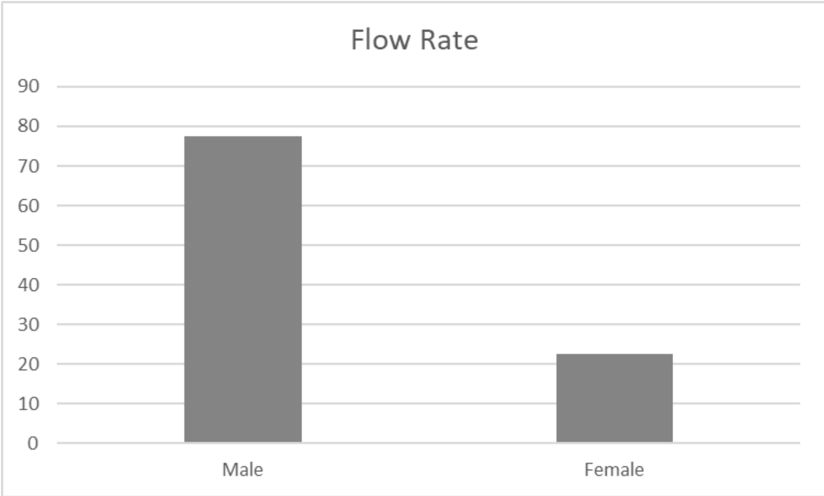

Figure 17 Gender Flow Rate

7. Journey Purpose

Based on the provided data, it is evident that cycling for recreational purposes significantly contributes to the higher flow rate. This can be attributed to both part-time and full-time cyclists engaging concurrently in cycling, increasing the flow rate. Additionally, leisure cyclists often ride their bicycles during standard timeframes, such as before and after work or on weekends.

In contrast, the flow rate is relatively low for students, with only 4.23% and 1.06% using bicycles for their school commute. On the other hand, a notable proportion of individuals, approximately 13.35%, prefer cycling as a means of transportation to and from work, while 8.33% incorporate cycling as part of their work responsibilities. Commuters who cycle during peak hours in congested areas may experience slower flow rates due to increased traffic.

Therefore, it can be inferred that the primary factor contributing to the higher flow rate among part-time and full-time cyclists is the recreational nature of their cycling activities, primarily undertaken for enjoyment rather than commuting.

Table 29 Journey Purpose

S.No	Purpose	Frequency	Flow rate
1	Commuting to/from work	101	13.35
2	Journey as part of work	63	8.33
3	Not known	159	21.01
4	Other (Leisure and Entertainment)	394	52.02
5	Pupil riding to/from school	32	4.23
6	Taking pupils to/from school	8	1.06
	Total	757	100.0

4.0 Results and Discussion

This section calculates the correlation tests between the variables using Spearman and Pearson Correlation Tests.

1. Spearman Correlation Test

The correlation coefficient, ranging from -1 to +1, provides valuable insights into the relationship between variables. A value of -1 indicates a perfect negative correlation, implying that as one variable increases, the other decreases. A correlation coefficient of 0 signifies no relationship between the variables, while a value of +1 represents a perfect positive correlation, suggesting that as one variable increases, the other also increases proportionally. The equation is given below:

Equation 1

$$r_s = 1 - \frac{6\sum d_i^2}{n(n^2-1)},$$

Where n= number of observations,

Di= rank difference between each observation

2. Pearson Correlation Test

The Pearson correlation test is a statistical technique used to assess the strength and direction of the linear relationship between two continuous variables. It is widely utilized in research to examine the extent of the association between two variables. The equation is given below:

Equation 2

$$\mathbf{r} = \frac{\mathbf{n(\sum xy) - (\sum x)(\sum y)}}{\sqrt{\mathbf{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}}}$$

Where n represents the total number of observations in the dataset, ∑xy indicates the sum of the cross-products of the deviations of each variable from their respective means. Additionally, ∑x and ∑y represent the sums of the deviations of x and y from their respective means. Moreover, ∑x^2 and ∑y^2 signify the sums of the squared deviations of x and y from their respective means.

The correlation tests performed among the variables are given below:

Table 30 Correlation Tests

S.No	Variable	Correlation Performed
1	Monthly Variation	Spearman
2	Hourly Variation	Spearman
3	Daily Variation	Spearman
4	Journey Purpose	Spearman
5	Lighting Variation	Pearson
6	Meteorological Variation	Pearson
7	Gender	Pearson

4.1 Monthly Variation

Table 31 Correlation of Monthly Variation

Variables	Obs.	O_{mw}	O_{wm}	Min	Max	Mean	Std
Flow Rate	12	0	12	4.000	12.500	8.325	2.919
Crash Rate	12	0	12	3.200	13.500	8.333	3.171

Where Obs= Observations, Omw= Observations with missing data, Owm= Observations without missing data, Min= Minimum, Max= maximum, Std= Standard Deviation.

The monthly correlation between crash and flow rates is 0.916, indicating a strong positive relationship between these two variables. This suggests that as the flow rate increases, the crash rate tends to increase as well, and conversely, as the flow rate decreases, the crash rate tends to decrease. The correlation is particularly evident during the summer months when both flow and crash rates peak.

However, it is essential to note that while the correlation is high, other factors may contribute to the increase in collisions during the summer. These factors could include changes in road conditions, higher volumes of tourist traffic, or adjustments in driving behaviours influenced by seasonal weather conditions (Chakrabarty and Gupta, 2013).

Table 32 Monthly correlation

Correlation matrix (Spearman):		
Variables	Flow Rate	Crash Rate
Flow Rate	**1**	0.916
Crash Rate	0.916	**1**

4.2 Hourly Correlation

Table 33 Correlation of Hourly Variation

Variables	Obs.	O_{mw}	O_{wm}	Min	Max	Mean	Std
Flow rate	24	0	24	0.370	9.240	4.166	2.895
Crash rate	24	0	24	0.100	12.200	4.163	3.579

Where Obs= Observations, Omw= Observations with missing data, Owm= Observations without missing data, Min= Minimum, Max= maximum, Std= Standard Deviation.

The correlation coefficient 0.942 reveals a strong positive relationship between hourly crash rates and flow rates. This suggests that the crash rate also tends to increase as the flow rate increases. This finding aligns with previous literature and data analysis, which indicate that the morning and evening rush hours, coinciding with office and school timings, experience higher traffic volumes.

The correlation test indicates that crash rates are likely to be significantly higher during these peak hours compared to other times when the flow rate is lower. Recognizing this relationship between time of day and crash rates highlights the importance of considering timing factors when advocating for bike safety improvements (Bopp et al., 2018). To enhance the safety of cyclists on the roads, city planners and transportation authorities may need to adapt infrastructure, regulations, and educational initiatives accordingly, taking into account the specific challenges posed during peak traffic hours.

Table 34 Hourly Correlation

Correlation matrix (Spearman):		
Variables	Flow rate	Crash rate
Flow rate	**1**	0.942
Crash rate	0.942	**1**

4.3 Daily Variation

Table 35Correlation of Daily Variation

Variables	Obs.	O_{mw}	O_{wm}	Min	Max	Mean	Std
Flow rate	7	0	7	10.300	16.400	14.271	2.715
Crash rate	7	0	7	10.700	16.500	14.286	2.042

Where Obs= Observations, Omw= Observations with missing data, Owm= Observations without missing data, Min= Minimum, Max= maximum, Std= Standard Deviation.

The correlation coefficient of 0.577 indicates a moderate positive relationship between the daily crash and flow rates, suggesting a connection between these variables. It suggests that as the flow rate increases, the crash rate also tends to increase, although not always in direct proportion. One possible explanation for this pattern is the heavier weekday traffic primarily driven by commuting. Weekdays typically experience a higher volume of people travelling to and from work or educational institutions, leading to an increased number of cyclists on the road during these times.

Several factors contribute to the higher flow rate of cyclists and crashes observed on weekdays compared to weekends. These factors include increased traffic from commuters, potentially hazardous cycling behaviours, and a significant proportion of inexperienced or less skilled cyclists on the road during weekdays (Clarke et al., 2007). The combination of these factors likely contributes to the higher crash rates during weekdays.

Table 36 Daily Correlation

Correlation matrix (Spearman):

Variables	Flow rate	Crash rate
Flow rate	**1**	0.577
Crash rate	0.577	**1**

4.4 Journey Purpose

Table 37 Correlation Of Journey Purpose

Variables	Obs.	O_{mw}	O_{wm}	Min	Max	Mean	Std
Crash rate	6	0	6	0.200	61.400	16.667	23.023
Flow rate	6	0	6	1.060	52.020	16.667	18.695

Where Obs= Observations, Omw= Observations with missing data, Owm= Observations without missing data, Min= Minimum, Max= maximum, Std= Standard Deviation.

The Spearman correlation coefficient of 0.943 indicates a strong positive correlation between the flow and crash rates based on the purpose of the journey. This suggests that as the flow rate for different travel purposes increases, the crash rate also tends to increase, and vice versa. Among all travel purposes, entertainment and leisure have the highest flow rates, and the crash data aligns with this by showing the highest crash rates for this purpose. The significant correlation coefficient supports this relationship.

The higher crash rates associated with entertainment and leisure travel purposes can be attributed to several factors. Part-time cyclists often ride alongside full-time cyclists for recreational purposes, increasing the likelihood of collisions (Prati et al., 2020). Additionally, part-time cyclists may be less familiar with the routes or traffic patterns, posing a higher accident risk. Moreover, during peak traffic, there is typically a higher volume of motorists on the roads, leading to increased traffic congestion and potential accident risks (Hojati et al., 2013). These factors collectively contribute to the higher crash rates observed during travel for entertainment and leisure purposes.

Table 38 Journey Purpose Correlation

Correlation matrix (Spearman):		
Variables	Crash rate	Flow rate
Crash rate	**1**	0.943
Flow rate	0.943	**1**

4.5 Lighting Variation

Table 39 Correlation of Lighting Variation

Variables	Obs.	O_{mw}	O_{wm}	Min	Max	Mean	Std
Crash rate	2	0	2	16.910	83.090	50	40.259
Flow rate	2	0	2	18.530	81.470	50	36.306

Where Obs= Observations, Omw= Observations with missing data, Owm= Observations without missing data, Min= Minimum, Max= maximum, Std= Standard Deviation.

In this case, there is a strong negative correlation between the two variables, with a correlation coefficient of -0.982. This indicates a significant negative association between the Crash and Flow rates. It suggests that the Crash Rate tends to decrease as the Flow Rate increases and vice versa. The Crash Rate is notably higher during daylight hours, which aligns with the findings from the Flow Rate dataset discussed earlier. It is also observed that the Flow Rate is significantly higher during the day.

The higher Crash Rate during daylight hours can be attributed to the increased presence of bicycles on the road. This heightened awareness among motorists encourages them to be more cautious and attentive while passing cyclists (Kaplan et al., 2019) . Additionally, the increased number of cyclists can contribute to slower traffic, making it easier for drivers to navigate and avoid accidents (Rubie et al., 2020). Overall, the negative correlation indicates that increasing the number of bicycles on the roads throughout the day while implementing appropriate safety measures can improve traffic safety.

Table 40 Lighting Correlation

Correlation matrix (Pearson):		
Variables	Crash rate	Flow rate
Crash rate	**1**	-0.982
Flow rate	-0.982	**1**

4.6 Meteorological Variation

Table 41 Correlation of Meteorological Variation

Variables	Obs.	O_{mw}	O_{wm}	Min	Max	Mean	Std
Crash rate	2	0	2	7.5	92.5	50	53.8
Flow rate	2	0	2	21.74	78.26	50	29.8

Where Obs= Observations, Omw= Observations with missing data, Owm= Observations without missing data, Min= Minimum, Max= maximum, Std= Standard Deviation.

There is a significant negative correlation between the Crash Rate and the Flow Rate, as indicated by the Pearson correlation coefficient of -0.963. The crash data analysis revealed a notable decrease in collisions during severe weather conditions, supported by the correlation test results. This implies that as the Flow Rate increases during inclement weather, there is a decrease in the number of crashes.

One possible explanation for this finding is that individuals exercise more caution when driving in adverse weather conditions (Hranac et al., 2006). This heightened caution can contribute to safer driving practices and fewer accidents. Consequently, the negative correlation between the Crash Rate and the Flow Rate during severe weather suggests drivers are more likely to adopt cautious driving behaviours, reducing collision risk. Overall, the correlation analysis reinforces the observation that people tend to drive more cautiously during inclement weather, resulting in a lower Crash Rate as the Flow Rate increases in such conditions.

Table 42Meteorological Correlation

Correlation matrix (Pearson):

Variables	Crash rate	Flow rate
Crash rate	**1**	-0.963
Flow rate	-0.963	**1**

4.7 Gender Variation

Table 43 Correlation of Gender

Variables	Obs.	O_{mw}	O_{wm}	Min	Max	Mean	Std
Crash rate	2	0	2	7.5	92.5	50	53.8
Flow rate	2	0	2	21.74	78.26	50	29.8

where Obs= Observations, Omw= Observations with missing data, Owm= Observations without missing data, Min= Minimum, Max= maximum, Std= Standard Deviation.

There is a strong negative correlation of -0.761 between crash and flow rates for both males and females. This indicates that the crash rate tends to decrease as the flow rate increases for males and females. The correlation analysis suggests that increasing the flow rate for both genders can reduce the crash rate.

One possible explanation for this finding is that as the flow rate increases, traffic tends to move at a slower pace, which can contribute to a decrease in the probability of crashes. Factors such as a higher representation of male cyclists on the road, variations in riding behaviours, or differences in risk-taking tendencies between men and women may also play a role in this association (Garrard et al., 2012). In conclusion, the strong negative correlation between crash and flow rates for males and females suggests that an increase in the flow rate can contribute to a decrease in the crash rate. This highlights the potential benefits of promoting and accommodating more cyclists to enhance overall safety.

Table 44 Gender Correlation

Correlation matrix (Pearson):		
Variables	Crash rate	Flow rate
Crash rate	**1**	-0.761
Flow rate	-0.761	**1**

5.0 Conclusion

This report aimed to calculate the effect of variables on cyclist safety, such as lighting, meteorological variations, and traffic flow. The crash data is calculated in the first section, followed by the flow data in the region Tyne and Wear. The existing safety models ignore or do not include these variables. These variables are crucial in establishing mode preferences and promoting cycling as a safe and environmentally friendly means of transportation. Even though they might not appear significant to motorists, these aspects impact safety, mode, and route decisions and should thus be considered in safety models.

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