A BIKEABILITY INDEX FOR LAST-MILE ELECTRIC CARGO CYCLES

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Abstract

A scoring index is developed to analyze the attractiveness of bike routes in urban areas for last-mile logistics using electric cargo cycles (ECCs). This thesis creates the ECC scoring index using a survey with participants riding on four routes within the York University Keele Campus. A literature review is conducted to identify twelve variables for the score. Data is collected using devices including a GPS-connected smartphone, a Gyroscope and a GoPro camera. Participants are asked to rate specified variables on infrastructure, safety and behaviour. The analytical hierarchy process is used to compute the weights for each variable using pairwise comparisons. Variables with the highest weights out of 100% include collision risk (24.3%-25.5%), visibility (11.1%-13.0%) and pavement condition (9.9%-12.4%). A simplified scoring index is derived using variables that could easily be applied to other routes to test its transferability.

Dedication

I dedicate this work to my parents and friends, that supported me throughout my journey.

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List of Abbreviations

Terms	Explanation
AHP	Analytical Hierarchy Process
BCI	Bicycle Compatibility Index
BEV	Battery-Powered Electric Vehicle
BLOS	Bicycle Level of Service
E-Bike	An Electric Pedal Assist Bicycle
ECC	Electric Cargo Cycle
GIS	Geographical Information System
GHG	Greenhouse Gas
GPS	Global Positioning System
ID	Identifier
ISO	International Standards Organization
LOS	Level of Service
PIEV	Perception, Identification, Emotion and Volition Time
PM Peak	Afternoon Period with High Traffic Volume
O-D	Origin-Destination
RFP	Remaining Functional Period
RP	Revealed Preference
RSP	Remaining Structural Period
SP	Stated Preference

Chapter One: Introduction

1.1 Research Motivation

Infrastructure is often measured in the transportation field based on its mobility performance. For example, the Highway Capacity Manual provides a bicycle level of service (BLOS) measurement for road segments, at intersections and on multi-use paths for cyclists (Transportation Research Board, 2017). A BLOS of A means cyclists can move freely without needing to change their speed in response to other road users, whereas BLOS of F means their speed is heavily limited and forward direction travel is achieved via short movements. The BLOS for multi-use paths uses the number of bicycles per hour to categorize the LOS whereas on road segments and intersections variables related to roadway and intersection geometry, pavement condition, travel time and number of passings are collected under steady traffic flow conditions to compute the BLOS.

Outside of engineering, a scoring index is often used as a tool to analyze the attractiveness of the built environment in many urban areas for different modes of travel, such as biking, walking, and public transit. A walk score is a tool originally developed to "encourage people to make sustainable choices about where to live" and is also used to analyze sustainable housing (Kitchin, 2014). Walkability is the capacity of the built environment to enable walking while having pedestrian-friendly access to destinations (Moura, 2017). Similarly, bikeability represents the ability of the built environment to allow cycling while enabling bicycle access to destinations. For an environment to be bicycle-friendly, Ram & Hall (2017) consider several variables, such as traversability, visual appeal, physical safety, and accessibility to multimodal connections.

The use of conventional courier trucks to deliver goods in urban areas has resulted in curb lanes being blocked by courier trucks due to the lack of on-street parking (Guse, 2022). This results in road users experiencing traffic congestion with users on single-lane roads and bike lanes impacted the most. This experience is exacerbated during peak travel periods due to on-street parking being fully occupied and establishments ship and receive most of their packages during those periods. The current strategy to address these blockages is through parking ticket enforcement. Overtime, courier companies have arranged with municipalities to resolve large amounts of tickets through global resolution where the number of tickets to be paid is reduced but also ensures the remaining tickets owed are paid and offending trucks are not towed (Perkel, 2019; Rinde, 2023; Sentencing

Council, 2017). In the city of Toronto, this has resulted in up to 30% of parking tickets incurred by couriers from global resolution being thrown out, leading to lost revenue for the city (Spencer, 2015). The city of Toronto allows couriers to have a citywide parking permit that enables them to park in "No Parking" designated areas but not in "No Stopping/Standing" areas (City of Toronto, 2011). This permit is a short-term solution, and as the city continues to densify, the number of no-stopping regions increases, forcing couriers to violate their permit's conditions.

Many courier trucks are currently diesel or gasoline, which emit greenhouse gas emissions (GHGs) into the environment when they are in use. GHG emissions have been steadily rising over the past two centuries, and the excess emissions have led to global temperatures rising, resulting in climate change (NASA, 2023). In an urban area the size of New York City, courier trucks travelling 98.9 thousand vehicle kilometres produced 14.4 metric tons of GHGs per day in 2021 (Yang et al., 2023). The same study found that the transition to using existing bike infrastructure by courier companies such as UPS in New York to conduct deliveries using electric cargo bikes reduced GHG emissions by 18.5% or 2.3 metric tons per day. New York City is also sensitive to courier truck blockages in its denser areas, as well as the lack of on-street parking and delivery zones (New York City Department of Transportation, 2023). To reduce courier truck blockages, overall traffic congestion and greenhouse emissions, cities have allowed couriers to deploy Electric Cargo Cycles (ECCs) on bike lanes and city streets.

The adoption rate of ECCs for last-mile logistics has been continually increasing over time. FedEx has worked with the city of Paris to deploy ECCs as a part of their urban logistics fleet since 2009, while DHL and FedEx have deployed ECCs as part of their carrier fleet in multiple metropolitan areas such as New York City and London (FedEx, 2009; City of New York, 2019; FedEx, 2020). Urban regions in Canada have also begun ECC pilots, such as Montreal's project Colibri Maisonneuve with Purolator and Vancouver's collaboration with FedEx (City of Montreal, 2022; Foote, 2020). The use of ECCs provides a zero-emissions and smaller-sized alternative to traditional truck delivery in urban areas with the potential to scale up to meet the demand for E-commerce deliveries to residential and commercial businesses.

1.2 Research Problem

The increasing adoption of ECCs has brought up challenges between the vehicles and the urban infrastructure. Road safety between commercial cargo cyclists and other road users is a concern due to their increased size and speed compared to a standard bicycle while sharing the same infrastructure. A survey conducted of 34 commercial cargo cyclists in the city of Montreal found that 16 of the survey participants declared that they experienced frequent near misses or minor injury collisions (Lachapelle et al., 2021). The actions that caused these injuries included car doors opening without checking for oncoming traffic and cars travelling too close to the cyclist. Despite that, all of the survey participants indicated their preference for using routes with reduced vehicle and cycling exposure as well as protected lanes. Cyclists prefer separation and the presence of dedicated cycling facilities and infrastructure along their routes (Caufield, Elaine, & McCarthy, 2012; Hull & O'Holleran, 2014; De Sousa, Suely, & Ferreira, 2014). Using surveys to collect data assists in identifying cyclist preferences by capturing behavioural variables that are more challenging to measure with traffic performance (Gaille, 2020). This survey data can proactively address existing issues and justify solutions while gaining the support of decision-makers (Ontario Human Rights Commission, 2023).

Previous studies related to ECCs focused only on the effects of their performance due to changes in the urban infrastructure, including types of biking infrastructure and topography. Thoma and Gruber (2019) concluded that infrastructure constraints were an increasing barrier over time among users. However, they did not provide a quantitative analysis but rather highlighted it as a critical factor in future policy decisions around ECCs. Some studies looked at the operational feasibility of ECCs based on carrying capacity, type of delivery and the number of deliveries that can be made in a specific timeframe (Conway, Cheng, Kamga, & Wan, 2017). Yet they do not factor in the effect that user perception and traffic flow characteristics have on ECC usage. While studies have been able to quantify user perception of cycling through means such as the level of comfort, these studies use the cumulative weight of vibrations experienced by the ECC, which depend on the condition of the pavement and thus are due to changes in the urban infrastructure (Gao, et al., 2018; Qiu & He, 2018). The studies do not consider the effect of user perception of these variables that would play a role in cycling route preference.

Previous walk and bike scores do not consider specific characteristics of a route, such as comfort and safety. One such widely used score known as The Bike Score© uses data such as the number of bike commuters, the type of cycling infrastructure available and the number of destinations that are accessible by cycling (Walk Score, 2023). Similarly, the United States National Cooperative Highway Research Program developed a GIS-based accessibility score for various transport modes, including cycling, by considering users' mode choice preference, travel time and accessibility to the origin and destination (Kuzmyak et al., 2014). The Bike Network Analysis tool measures how well biking connects people to attractive destinations. The tool considered the traffic volume on roadways as well as the distance and time it would take for a cyclist to reach destinations, including work, school, jobs, healthcare, commerce, and transit hubs (People For Bikes, 2023). The tool assumes that lower traffic volume would result in a safer road for cyclists. However, this may not always be the case, as a low-volume road with poor visibility and a lack of biking infrastructure can be less safe than a high-volume, high-visibility road with cycling infrastructure (Oikawa et al., 2019). While these scores consider many essential variables in assessing the most bikeable routes, they focus on infrastructure-based variables and require decision-makers to infer if the route is comfortable and safe.

Scoring metrics tend to use a small number of variables that are more evidence-based and can be visualized, such as travel time and the presence of cycling infrastructure (Winters et al., 2013). This leaves out variables that can still contribute to affecting the score, such as safety and comfort. The use of a route choice model to identify the statistical significance of the variables affecting decision-making has been commonly used in transportation but rarely applied to scoring metrics such as bikeability indices (Choi et al., 2020; Chen et al., 2017). Some existing scoring metrics use a regression model to compute the weightings or have participants assign a weighting and then apply the average of each participant's weight (Van Dyck, et al., 2012; Winters, Brauer, Setton, & Teschke, 2013). These scores use techniques that are more challenging to determine weightings for safety and behavioural variables. One method of determining the weights for these variables is through pairwise comparisons. The analytic hierarchy process (AHP) is a method that uses pairwise comparisons to identify the relative importance of each variable which weights are computed followed by determining the ranks from aggregating the weightings (Sander, 2010).

This thesis contributes to the existing work on commercial ECCs by developing a new type of bike score index aimed at electric cargo cycle (ECC) users and courier companies using ECCs as part of their last-mile logistics fleet. There is no existing bikeability score created for the unique requirements of ECCs. The score considers multiple variables related to active transportation assessment, including the relationship between characteristics of infrastructure, traffic flow, user perception and level of comfort. The comfort of a rider becomes more difficult for ECCs compared to traditional bikes due to the addition of heavier cargo. In addition, ECCs often have two wheels at the front. This physical attribute makes it more difficult for ECCs to avoid pavement distresses such as cracks, holes, and bumps. The weights are developed using the AHP.

1.3 Research Goal and Objectives

The goal of this research is to develop a new type of bike score index aimed at electric cargo cycle (ECC) users and courier companies using ECCs as part of their last-mile logistics fleet. This score is referred to herein as an ECC score. The purpose of the ECC score is to highlight favourable routes for ECC usage based on user perception. The thesis focuses on the following objectives:

1. Conduct a literature review on existing last-mile electric cargo cycle (ECC) programs and the different methods of scoring metrics in transportation,

2. Implement a field-based survey for data collection that allows respondents to experience and rate the quality and selection of four routes using an ECC,

3. Analyze the survey inputs to assess patterns for categorizing cyclists,

4. Develop an ECC score that can measure the suitability of routes for electric cargo cycles.

The first objective identifies appropriate variables to characterize the attractiveness of a route for ECCs. This is important because existing scoring metrics in transportation use different variables that affect specific modes of transportation more than others, such as slope, which affects bike routing more than truck routing. ECCs share similarities with traditional bicycles, and thus, previous literature on scoring metrics and variables discussed for bicycles may have a similar importance that can contribute to developing the ECC score. This review looks at both infrastructure-based, safety and behavioural variables.

The second objective is to develop a field-based survey to collect data for the score. This is important because the ECC is an emerging mode of transportation that is unfamiliar to the majority of the population. Allowing participants to directly experience the ECC provides for a more accurate response through the survey. Choosing a mode of travel is not solely determined by performance metrics such as the time it takes to reach your destination but also by how safe and comfortable it is to use. The field survey helps to capture this by having respondents rate the individual variables, collect quantitative data on the variables and rank the routes depending on the performance of each variable. This results in a score which is reflective of the priorities of the participant captured through the variables.

The third objective involves analyzing the survey inputs to assess trends and patterns. This is important because it allows for verifying if certain variables, such as the cycling vibrations, can describe a route as accurately as the participant's comfort rating. The trends and patterns identified can be used to categorize participants into different cyclist groups and identify the patterns associated with each group. This also allows us to identify how accurately the participants responded to the survey and identify outliers or participants who were not interested. This allows uninterested participants to be removed from the dataset, improving the accuracy of the data.

The fourth objective is to develop an ECC score that can be used on other routes and can be replicated by other decision-makers. Transferability of the score represents its ability to scale based on different conditions and variables while producing a score between 0 and 10 that identifies the best route option. This is important because the score is only useful as a tool if it can be used on routes with different orders of magnitude, such as using a set of routes that are a few kilometres long or routes that are dozens of kilometres long. A score that does not account for this results in short routes having all low scores and long routes all having high scores where a clear best route cannot be identified. This requires the score to be standardized in which the weights that are assigned are equal or between the smallest of the routes and the largest of the routes or other realistic boundaries. A simplified score is developed to maximize the score’s ability to be transferrable. Certain variables that do not describe the routes well or have too much variation have been removed from the simplified score.

The score can assist decision-makers of ECC logistics fleets in planning delivery routes more efficiently to take advantage of cycling infrastructure while minimizing travel time delays and conflicts with other road users. As mentioned previously by LaChapelle et al. (2021), some logistics companies financially incentivize commercial cargo cyclists to use the more direct albeit less safe and more congested route to perform the delivery. Navigating inefficient and unsafe routes can detract couriers from using the bikes to perform deliveries, which would result in underutilization of the fleet and a poor perception of ECCs by stakeholders. Using the score to develop more efficient delivery routes would result in improved stakeholder perception of ECCs as an alternative to last-mile logistics in urban areas.

1.4 Scope and Thesis Structure

This research is conducted on the York University Keele Campus in the city of Toronto. The data is collected through a field survey where participants ride a tricycle-style cargo cycle with electric pedals to assist with a near-empty payload on four routes between an origin point and a destination point within the campus. These routes consisted of local roadways with and without cycling infrastructure (bike lanes, sharrows, etc.) and pedestrian multi-use pathways. The ECC score is developed from weights using data collected from the field study, which includes instrument data of the ECC on the routes as well as survey data which consists of participant cycling experience and demographics, rating of cycling variables, pairwise comparisons of the variables and rankings of the four routes. The data is based on the state of the urban infrastructure (pavement, signs, traffic signals) of the routes at the time of data collection.

This research pertains only to a three-wheeled electric cargo bike with a front-end cargo trunk. The score does not fully reflect the use of other types of cargo bikes, including two-wheeled style bikes and trike-style bikes with partially or fully protected enclosures for the cyclist. The score does not pertain to the use of a cargo bike with a fully loaded trunk because the participants used to gather the data are of varying physical capabilities and had little to no experience using the ECC compared to experienced participants. The routes do not include arterial roadways due to the study area's location southwest of an industrial area bordered by major arterial roadways with no cycling infrastructure and a high truck volume with high posted speeds. These conditions are difficult to cycle in and can detract participants needed for the study. The score does not consider the effects of slope due to the routes being on flat terrain. The score also does not consider the effect of battery capacity or battery efficiency due to the routes being of shorter distances of up to 2 km each, with the ECC able to travel up to 75 km before needing to recharge the battery.

The rest of the thesis is outlined as follows. Chapter 2 is a literature review which discusses existing last-mile ECC programs, and the methods of scoring metrics in transportation research and planning (e.g., bike score, bikeability index). It also discusses the variables that impact the attractiveness of a route for ECCs, field survey methods and existing models developed for bikes, particularly models focusing on ECCs. Chapter 3 discusses the data collection methods, which include the procedure for selecting a set of four routes between an origin and destination pair and identifying how the variables are collected and measured for the field study. Chapter 4 discusses the field survey setup and how the AHP weights and route choice model are developed. Chapter 5 looks at and discusses the raw survey and instrument outputs. Chapter 6 discusses the results from the created AHP weights and the Route Choice Model. It also proposes a simplified ECC Score focused on transferability. Lastly, Chapter 7 summarizes the limitations, future research and applications of the score.

Chapter Two: Literature Review

2.1 Electric Cargo Cycles in Urban Areas

There is a large number of emerging ECC pilot programs in North America as part of emission reduction efforts by cities to slow down climate change (NASA, 2023). ECC pilot programs and permanent programs in different urban areas utilize various policy and planning considerations. In North America, ECCs are currently being deployed as a part of a pilot program in most major cities. The City of Toronto began a pilot program for ECCs in 2021, which allowed for the use of electric cargo cycles on bike lanes, multi-use paths and city streets (City of Toronto, 2021; Ministry of Transportation Ontario, 2021). The ECCs are allowed to travel up to a maximum speed of 32 km/h using the electric assist (Ministry of Transportation Ontario, 2022). ECCs in Toronto must share the biking infrastructure with pedal-only bicycles and other micro-mobility vehicles. ECCs can be queued behind slower-moving bicycles, resulting in longer travel times for couriers. Canadian Cities such as Montreal and Vancouver have had ECC pilot programs since 2019. Montreal's project Colibri Maisonneuve reduced the number of delivery trucks performing last-mile deliveries to businesses from 5 trucks to 1 truck and 5 ECCs while lowering operating costs by up to 40% (City of Montreal, 2022; Lyster, 2021). Vancouver's cargo bike pilot program offers financial rebates of up to $1,700 to businesses that own an ECC and allows their use for food stalls, street shops, and event vending with a permit (City of Vancouver, 2022). The city requires ECCs used for goods delivery service to be registered with the town under a bike courier licence.

Studies have been produced in the City of Seattle following the introduction of an ECC pilot program. In Seattle, electrically assisted bikes, including ECCs, are allowed to travel on sidewalks and pathways, provided that the electric assist does not result in the bike exceeding 20 mph (Morrison, 2020; Washington State Department of Natural Resources, 2018). Bikes that exceed this speed are not allowed to be used on city sidewalks and pathways. Seattle also has hilly terrain, and despite the challenges of cycling up and down hills, the city still has a sizable number of commuting cyclists, at 158,000 or 29% of the adult population (Seattle Department of Transportation, 2013). Seattle's bike share fleet did not consist of electric pedal-assisted bicycles, which would have compensated for the difficulty in cycling uphill and would have increased cycling demand.

Other American cities also have ECC pilot programs, such as New York City and Portland in 2019 (City of New York, 2019; Bike Portland, 2019). In 2023, New York City approved ECCs with four wheels that are up to 48 inches wide compared to the previous three-wheel and 36-inch width maximum (New York City Department of Transportation, 2023). This allows for a single box truck to be replaced by two ECCs of the maximum size, which would result in an emissions reduction of 14 tons per year or a reduced distance of 49,684 vehicle kilometres travelled.

In Western European countries, ECCs are a more established and widely adopted form of transportation for last-mile goods movement. The city of Paris, France, is an early adopter of ECCs for last-mile delivery in collaboration with FedEx in 2009 (FedEx, 2009). Today, Paris has been operating ECCs as part of their urban logistics fleet on all of the major couriers, including the country's national courier, La Poste (La Poste, 2022). The adoption of ECCs continues to increase in Paris, with La Poste's goal to have 100% carbon-free deliveries by 2025. This is conducted to meet the 2015 Paris Agreement goals, which aim to limit greenhouse gas emissions to a peak of 1.5 °C above pre-industrial levels by 2025 (United Nations, 2015). A study by Koning & Conway (2016) assessed the changes in Paris' transportation policy involving commercial goods and found that pro-bike policies have helped to change the mode commonly used for last-mile delivery in Paris from delivery vans to cargo bikes. By switching to cargo bikes, the city has saved €0.76 million per year with a reduction in CO_2 emissions by 3.5 tons/day between 2001 and 2014 (Koning & Kopp, 2014; Koning & Conway, 2014). Congestion in the city has also decreased due to the adoption of ECCs, which removed 3222 daily vehicle trips and saved on average 2 hours of annual travel time for road users (CGSP, 2013). As a result, the long-term benefits of adopting ECCs include reduced carbon emissions and economic and travel congestion savings.

A study on the benefits of ECCs in London, UK, showed that ECCs can deliver 60% more packages per hour than delivery vans or courier trucks due to lesser impacts caused by impedances such as limited parking and the walking distance from parking to the establishment (Active Travel Academy, 2021). The study concluded that 50 minutes per day more was spent looking for parking for trucks compared to ECCs, allowing for a greater number of packages that can be delivered. However, due to the lower capacity of ECCs, only 25% of the packages could be delivered by an ECC in a single tour before needing to reload.

In the Netherlands, ECCs are a popular mode of transport for people living in urban areas, with cycling representing the second most common mode of transport in the country at 36% compared to automobiles at 45% (Boterman, 2020; The Netherlands: Ministry of Transport, 2009). In urban areas, this share increases to 38% in Amsterdam and up to 46% in the city of Zwolle (Bosch, 2014). ECC usage represents 2% of the total mode share in Amsterdam due to the higher upfront cost of owning an ECC compared to a conventional bike (Boterman, 2020). Amsterdam is one of the few cities to have an ECC bike share program, with over 850 ECCs available (City of Amsterdam, 2024). The city also allows residents to reserve ECCs for free to transport bulk and hazardous waste to recycling centres to encourage residents to practice sustainable waste disposal (Iolov, 2023). Compared to Europe, Canada is further behind in terms of ECC policy and infrastructure adoption. For ECCs in Canada to gain a similar mode usage among people in urban areas like European cities, decision markers in Canadian cities need to improve existing policies and infrastructure to encourage ECC adoption.

2.2 Infrastructure-Based Variables

European cities often have a higher percentage of the population using bikes and ECCs. In Toronto, Canada, the cycling mode share is 20% compared to London, UK, where cycling overtakes car usage at 40% (City of Toronto, 2019; Reid, 2023). To increase ridership, variables that influence the attractiveness of cycling routes can be improved to reduce the physical and mental barriers for people to cycle. Cycling variables can be divided into three broad categories, including infrastructure-based variables, safety-based variables, and behavioural variables, such as comfort and enjoyment. This section discusses the infrastructure-based variables, while Section 2.3 discusses the safety-based variables and Section 2.4 discusses the behavioural variables.

Previous studies have considered different infrastructure and safety-based variables that can affect cycling route choice to develop their indices. Van Dyck et al. (2012) deemed built environment variables, including the presence of cycling and walking infrastructure and the number of destinations, while Osama et al. (2020) considered traffic volume and collision risk. Other studies included variables such as topography, presence of cycling parking facilities, travel distance and pavement condition (Kreen et al., 2015; Jensen et al., 2010; Giubilato & Petrone, 2012).

Travel distance is one variable that contributes to the attractiveness of a route. The 2016 Transportation Tomorrow Survey states that 24.1% of trips made by residents during peak periods had a total one-way trip distance of less than 7.0 km for the City of Toronto (Ashby, 2018). In addition, 14.0% of those trips comprised the use of active transportation modes such as walking and cycling. This means that cyclists who commute found that average shorter distance routes, routes with lower traffic volume and the presence of multi-use paths or dedicated cycling facilities were preferred. Aultman-Hall et al. (1997) conducted a GIS-based cycling study amongst cyclists in the city of Guelph, Canada and found that 37.5% of cyclist's routes were within 0.1 km of the shortest average distance route with an average deviation of 0.4 km from the shortest distance. Yet cyclists do not always follow the shortest route, with only 14.6% of the routes the cyclists took being identical to the shortest route. This is due to the effects of other variables along the route.

Travel time is another major variable that can affect route preference. A study conducted by Jensen et al. (2010) analyzed data from cyclists' average travel speed during AM Peak commute hours in the city of Lyon, France, collected under Lyon's bike-sharing system, the Vélo'v. It was found that in normal conditions among cyclists, the average speed travelled by bike was around 13.5 km/h, with shorter trips having an average speed of 15 km/h. Motor vehicles travelling in the same area had average speeds between 10 km/h and 15 km/h during the same period. This, when combined with the reduced time to park the vehicle and to walk to the final destination, results in bicycles exhibiting equal or lower travel times in the downtown area. The competitiveness of the travel time of bicycles compared to motor vehicles can encourage people to choose cycling as their mode of commute. A questionnaire survey conducted by Guo et al. (2017) in Ningbo, China, found that people with an average route travel time that was lower than 30 minutes were 7.77% more likely to use a bicycle compared to those with an average travel time longer than 60 minutes. It also found that the probability of choosing a bike to complete a multi-modal route was 20% greater among public transport users than among motor vehicle users. This means that cyclists value having lower travel times as it enables them to use bicycles for their travel mode more often. Lastly, it was found that 73.02% of respondents valued the travel time wasted due to taking poorer routes as a result of their cycling route patterns and that 90.62% valued the travel time saved due to better cycling routes. This shows that cyclists value the reduced travel times when cycling.

Travellers can have a perceived value of travel time and travel distance (Pourhashem et al., 2023). A study conducted on Toronto's cycling network using a multinomial logit route choice model found that a 1% increase in the number of multi-use pathways along the route led to a perceived decrease of 4.8% from the average travel distance (Li, Muresan, & Fu, 2017). The use of electric assist in micromobility vehicles such as ECCs can reduce the perceived travel time and travel distance experienced by the user (Bretones, et al., 2023). Micromobility vehicles fulfill the need for an in-between transportation option for short-distance trips that are perceived to be too short to justify paying for transportation but are perceived as too long to complete by walking (Bai & Jiao, 2020; Button, Fyre, & Reaves, 2020). This allows for fast and affordable travel to local destinations. A study by Christoforou et al. (2021) found that 72% of the public and active transportation users surveyed in Paris, France, switched to electric micromobility vehicles due to the perceived travel time savings despite a 6% increase in trip times for those using electric bike and electric scooter sharing due to the increased walking time to and from the rental facilities. Due to human psychological effects of time perception, the higher speeds and acceleration of ECCs compared to conventional bikes contribute to their attractiveness as an alternative mode of transport despite the observed time savings being minimal in some cases (Glicksohn, 2022).

The type of urban infrastructure can affect the routes chosen by cyclists. This includes the presence of cycling facilities such as bicycle parking or bike lanes, road classification such as arterial (high volume & high-speed traffic), local roads (low volume & low-speed traffic) and the presence of facilities for motor vehicles such as on-street parking. Cycling infrastructure can be divided into three broad categories: no cycling infrastructure, dedicated cycling lanes and multi-use paths.

In Canada, the no-cycling infrastructure category includes all roads where cyclists are allowed to bike except for highways and expressways. These roads have a high posted speed which is significantly higher than what an ECC can achieve and therefore are too dangerous for cyclists to share (City of Toronto, 2013). Sharrows, which are shared lane markings on streets, are included within the no cycling infrastructure category because of their lack of separation of bikes from motor vehicles, as they are meant to alert motor vehicles that the street is being shared with cyclists (US Federal Highway Administration, 2009). These types of roads tend to be used when there are very few roads with cycling infrastructure adjacent to the main route. Stinson & Bhat (2003) had a similar conclusion from their analysis of cyclist route choice preferences using a discrete choice model. It was found that cyclists preferred local roads followed by arterial roads, with a greater preference if the cycling facilities separated them from motorized vehicle traffic and avoided streets that allowed for parallel parking. The use of streets with no cycling infrastructure in combination with frequent bus public transit can deter the route from being used. Goodchild et al. (2023) studied ECC courier travel patterns in Seattle, USA and found that unprotected lanes located on major bus routes were frequently avoided by ECC couriers due to the frequent stops and the dwell time waiting for the bus to move.

Dedicated cycling infrastructure includes painted bike lanes and barrier-separated bike lanes that are constructed in the curb lane of a street and are marked only for use by bicycles and micromobility vehicles (Deegan, 2018). A cycling survey conducted by Howard & Burns (2001) found that 60.3% of streets used by cyclists were classified as arterial roads, yet 51% of the cyclists used streets with bicycle facilities present, including bike lanes and multi-use pathways. The study also noted that cycling commuters tend to choose routes with lower travel distances but still have cycling facilities present along the route. Goodchild et al. (2023) found that painted bike lanes were used less than barrier-separated lanes due to the narrowness of the existing lanes and the lack of connections between lanes on different streets. Cyclists would often choose to use the barrier-separated lanes, which were wider to accommodate the ECC's larger footprint compared to conventional bicycles.

Multi-use paths are wide paths separated from streets intended to be shared by cyclists and pedestrians (Delaney, Parkhurst, & Melia, 2017). Hood et al. (2011) broke down user route preferences according to three types of cycling infrastructure: multi-use bike paths, bike lanes and sharrows. The results showed that cyclists preferred bike lanes the most, followed by bike paths, due to their alignment with destinations on certain roads followed by multi-use paths. A key finding was that cyclists are willing to make travel distance detours between 0.49 km and 0.92 km to use routes with cycling facilities such as multi-use paths and bike lanes. A multinomial logit model looking at the effect of cycling infrastructure on route choice in Minneapolis, USA, by Krizek (2006) found that the presence of bike lanes is more appealing to cyclists despite the additional 16.3 minutes of travel time than off-street multi-use paths despite the minor increase in travel time of 5.2 minutes. Also, choosing not to use routes with street-side parking is somewhat valued despite an additional 8.9 minutes of travel time to avoid those streets. This negative relationship with multi-use trails is due to the trails running through residential areas of the city instead of through greenspaces or multi-use areas. They tend to have lower rates of bicycle use and lack destinations close to the path.

Topography is another variable that can affect cycling route choice. Wygonik et al. (2014) studied the change in bike-share demand across hilly areas in Seattle by using a weighted sum analysis of the slope. The study showed that for Queen Anne Hill, demand for bikes was still moderate due to the city center being situated on the hill, while Madison Valley, a primarily residential area, showed bike demand decreased when the slope was weighted higher than other decision variables in using a bike. Behrendt et al. (2021) conducted a study of electric pedal assist cycling on steep hills in Brighton, UK. The study showed that 75% to 90% of cyclists used the electric pedal assist for slopes greater than 8%, with almost all study participants reporting more manageable and effortless commutes using e-bikes. A bike route choice model conducted for San Francisco; an urban coastal city with steep topography found that cyclists would ride for an additional mile to avoid 100 ft of elevation gain over a shorter distance (Hood, Sall, & Charlton, 2011). Parkin discovered that topography has a significant correlation with a person choosing to adopt cycling for work-based purposes (Parkin, Wardman, & Page, 2008). Their study also found that a 10% increase in slope elevation resulted in a 10% to 15% reduction in cycling for work (Parkin, Riley, & Jones, 2007)

There are differences in the infrastructure variables considered for modelling certain types of vehicles. Route choice for cars focuses more on traffic-based variables in locations where the congestion on routes during high-traffic volume periods is the greatest (Cao & Zhang, 2016). The travel time is higher for cars due to the longer travel distance compared to bikes and the greater the impact a delay would have on the travel time of the route. For bicycles, while travel time-related variables can influence the choice of a route, other variables are important such as the safety of the cyclist, visible sight lines, and a direct path with connections to destinations and other parts of the cycling path network (Calvey et al., 2015). Bikes may use paths separated from city streets to minimize interaction with motor vehicles, but these paths can be less desirable if poorly maintained and negatively affect the variables listed. Route choice for E-bikes tends to focus on finding the safest and most accessible route instead of choosing the shortest route, with variables previously mentioned that affected conventional bicycles also applying to E-bikes (Cubells et al., 2023). E-bikes are less physically demanding to operate compared to traditional bikes while allowing for higher sustained speeds. Yet the preference for using cycling infrastructure as part of the route remains to have safer interactions with cars and pedestrians. The battery capacity and efficiency can also affect the route taken as steeper and longer routes tend to deplete the battery more when relying on electric assist compared to short and flat routes.

Infrastructure-based variables that can affect cycling route choice are travel time, travel distance and the type of cycling infrastructure. These variables are used in the thesis. The four routes have a predetermined travel distance. As a result, the travel speed is measured because it can affect route preference similarly to travel time. Variables that are not considered from this category include the slope of the routes due to the study area located on flat terrain and, the climate and weather on the route as the study is being conducted within a short period where the weather conditions are favourable for cycling (warm weather, low precipitation).

2.3 Safety-Based Variables

Road safety-related variables can also affect cyclist route preferences. The experience of being in or seeing a traffic collision or a near-miss conflict can influence a cyclist's use of alternative routes to prevent it from reoccurring. A traffic collision is defined as an event where a vehicle collides with another car, person, or object (Peden et al., 2020). Collision data is obtained from collision record databases or online dashboards (Abdulhafedh, 2017; Toronto Police Service, 2023). These databases mostly record cyclist collisions when a motor vehicle is involved in the collision and when a severe injury or fatality occurs. Cyclist collision data can also be obtained from online databases where cyclists can submit collision or near-miss experiences along with the location of the incident to inform other cyclists. These experiences are subjective because they are usually self-reported by the person involved in the incident and do not always reflect the safety risk a cyclist would experience on the route (Stulpnagel & Lucas, 2020).

A field survey conducted of thirty-four commercial cargo cyclists in the city of Montreal, Canada, surveyed a wide range of cargo cyclist users ranging from logistics messengers, short-distance moving companies and grocery delivery (Lachapelle et al., 2021). The survey showed that sixteen of the participants declared that they experienced frequent near misses or minor injury collisions. Nine of those participants experienced a severe injury while on the job. The actions that caused these injuries included car doors opening without checking for oncoming traffic and cars travelling too close to the cyclist due to the need to speed through an amber phase signal. All of the cyclists surveyed consistently wore the appropriate safety equipment, which has assisted in preventing possible deaths or more severe injuries. Self-reporting near misses is currently the most dominant technique for cycling near-miss studies and has led to a greater understanding of cycling ridership and safety measures (Jestico et al., 2016). Yet, the data gathered is limited by potential biases and inaccurate representation of cyclist groups and risk factors (Dozza & Werneke, 2014).

Cyclist visibility is another variable that affects the safety risks that cargo cyclists experience. A study conducted by Oikawa et al. (2019) looked at the variables that contributed to cycling-related collisions between bikes, passenger vehicles and delivery vehicles. The study noted that cyclists used local roads to avoid congestion, which lacked cyclist visibility or protected cycling infrastructure. Higher fatalities were experienced on local roads compared to arterial roads, which allowed cyclist visibility or separation from other road vehicles. Nearly all of the fatalities were from impacts to the hip instead of the head due to the hip being the least protected area of a cyclist. As cycling safety equipment focuses on the head and joints, a collision at slower speeds can still result in a life-threatening injury for the cyclist despite wearing protective equipment. The study shows that cyclist visibility is a significant factor in reducing collisions and suggests that the effect of infrastructure in reducing these accidents should be looked at.

Cyclists in urban areas of high vehicle motor traffic are more likely to have a higher risk of injury at mixed-traffic intersections than motor vehicle users. In the city of Montreal, Canada, 100 of 1000 accidents involving a cyclist and motor vehicle. Out of the 100 involved, 10 are hospitalized (Velo Quebec, 2005). 60% of these accidents occur at intersections (Miranda-Moreno & Nosal, 2011). A multivariate model developed by Miranda-Moreno et al. (2011) used geometric and collision data from Montreal. The results of the model found that cyclist safety is affected by traffic flow and cyclist volumes, especially when conducting right turn movements, with an increase of 1.65% in potential injuries from a 10% increase in right turns, which had a greater effect than left turns (1.01% increase per 10% increase) and through movements (1.24 % increase per 10% increase). Increases in bicycle volume did not noticeably affect the number of potential injuries. A cyclist would most likely want to avoid using a route with a high degree of motor-vehicle turning movements or where cyclist visibility is poor when conducting the movements themselves. This can lead to changes in the cyclist’s route choice. Routes with a more significant number of turns are more dangerous to use than routes with fewer turns due to the lower risk of potential injury with a motor vehicle.

While the visibility of the cyclist among other road users on a route is essential to consider, the ability for the cyclist to have clear sightlines of the route, vehicles, and infrastructure is also crucial as it allows road users to have full awareness of other road users when crossing an intersection (Austraroads, 2010). A study conducted by Hiscock & Johnson (2018) found that after the development of a clear sightline for cyclists along the Beaconsfield Parade intersection in Melbourne, Australia, the number of collisions decreased. Clear sightlines can also affect cycling behaviour. It was also found that clear sightlines would result in cyclists 33.6% more likely to slow down due to bicycle traffic and 17.9% more likely to slow down due to infrastructure, compared to 44.9% slowing down at intersections without clear sightlines. This allows cyclists to decrease their travel time by slowing down less and stopping less. This results in routes with clear sightlines being more favourable as part of a cycling route. Infrastructure such as roundabouts that prioritize cyclist and pedestrian traffic are an example of this as they provide clear sightlines for both cyclists and motor vehicles while making it easier to predict each other trajectories through the intersection (Cumming, 2012).

Clear sightlines can also reduce the risk of car-dooring on routes with on-street parking. A study by Cumming (2012) found that car-dooring in the city of Melbourne accounts for 10% of cyclist collisions. Cyclists would need to have at least 1 m of clear sightline distance between themselves and the door zone of the parked car to allow for enough time to react to a door opening safely. This, however, negates the advantage of being able to cycle past a queue of motor vehicles by weaving in between parked cars, as it forces the cyclist to travel primarily in a straight line. The presence of vegetation and obstructions such as signs and billboards can affect the available sightline distance. A field study conducted by Gonzalez-Gomez & Castro (2020) looked at the changes in sightline distance due to obstructions for bicycles on a roundabout. It was found that vegetation next to crossing areas hindered cyclists' sightlines to spot pedestrians at the crosswalk beyond an average distance of 5 m to 10 m away from the crosswalk compared to a crosswalk with no vegetation, which allowed an average sightline of 47 m and 55 m for the yielding line. Routes with obstructions can result in routes being less desirable to cyclists due to the need for them to reduce their speed and be more cautious, resulting in a longer travel time using that route.

Collisions between trucks and vulnerable road users such as cyclists can occur, especially during the peak periods in urban areas. This is sometimes due to truck drivers not checking their blind spots when performing turns (Niewoehner & Berg, 2005). These collisions typically occur in urban areas when a truck is turning right from a full stop (waiting for a traffic light), which results in the cyclist overtaking the car due to the bicycle's higher acceleration rate (Kaplan & Prato, 2013). Routes with physically separated cycle lanes can decrease these collisions, but if the separation is too close to the turning lanes, an increased risk of collisions can occur (Vandenbulcke et al., 2014). A study conducted by Jansen & Varotto (2022) found that truck drivers were more likely to check their blind spots for cyclists when lanes were visibly marked and advanced stopping lanes were present, as well as zebra or protected crossings. In addition, visual obstructions (buildings, billboards, and vegetation to a lesser degree) prompted the truck driver to check more often than in non-obstructed areas. Routes with lower than 50 km/h posted speed limits also prompted more checks by truck drivers to ensure there were not any vulnerable users (bicycles, scooters) present in the blind spot. These trends can impact the routes a cyclist would take as well as areas where road users have heightened awareness of other traffic, which can lead to a safer experience when navigating the intersection, especially on routes where there are an unavoidably large number of turns, such as with last-mile delivery routes.

The number of passing vehicles and pedestrians can affect the level of safety that cyclists feel on the route (Hull & O'Holleran, 2014; Chataway, Kaplan, Nielsen, & Prato, 2014). A significant volume of vehicles weaving in and out of curb lanes and on-street parking results in the cyclist's space being encroached on, increasing the likelihood of a collision. A high pedestrian traffic volume where there is a higher occurrence of random movements by pedestrians through the cyclist's space can also increase the likelihood of a collision. A study carried out by Apasnore et al. (2017) had participants in Ottawa, Canada evaluate on the Likert scale how dangerous the passing event is between a bicycle and another mode of transport, such as a pedestrian, car, or bus. The study was used to develop a passing distance model, which found that shared roads with on-street parking had the most passing events and that the events tend to be considered more dangerous than on wider arterial roadways. A study by Zhao et al. (2013) found that the number of passing vehicles was more significant on three and four-lane roads, which made it easier to overtake other cyclists than on narrower 2-lane roads, while the number of passing vehicles decreased as traffic volume increased.

A near miss is defined as an event when a cyclist almost collides with a vehicle, person or object but does not occur while escaping physically unscathed (Sanders, 2015). Near-miss data involving cyclists is primarily collected from survey interviews. Crowdsourced data on cycling collisions and near misses is available on services such as BikeMaps.org but requires the user to subjectively self-report the collision or near miss (Branion-Calles et al., 2017). A study using crowdsourced cycling near-miss data for 9 Canadian cities found that over 20% of the near misses are from dangerous passing by a motor vehicle or overtaking the bicycle midblock with right-turning cars and failing to stop or yield to the bike being the second (18%) and third (15%) highest cause of near misses respectively (Laberee et al., 2021).

A study conducted by Howard & Burns (2001) in the city of Phoenix, USA, looked at the influence of near misses and their effect on a cyclist's perception of a safe cycling route as well as how it affected route choice decisions. It was found that 22% of respondents would switch their route if they had an accident along their current commuter route and that 36.3% of respondents have been in an accident. Most of the respondents felt their current routes were safe at 71.7%, which resulted in a lower preference to change routes if an accident were to occur along them. The spatial analysis of the survey data and GIS data of the city's cycling and road network found that commuters chose routes based on a combination of safety, low travel time, and a direct route to their destination. This shows that near misses and accidents can affect a cyclist's route preference, and its effect can impact whether a route is safely bikeable for them.

Tracking cyclists' near misses can also be done objectively. A study by Li et al. (2023) developed a benchmark for cycling near misses from video recording streams in Melbourne, Australia. The benchmark defines a near miss when there is a minimum distance of less than 1 m between a vehicle and bicycle on roads with speed limits below 60 km/h or a minimum distance of 1.5 m on roads with speed limits above 60 km/h. This is in line with the City of Toronto's bike-passing law, which requires vehicles to keep at least a 1-m distance between themselves and a passing cyclist (City of Toronto, 2023). This method can also be performed manually by watching recorded cycling footage, which becomes time-consuming for a city-wide analysis. Computer vision strategies can used to automate this for city-wide analysis but are limited by the amount of data and image processing that can be conducted, as well as requiring multiple cameras at an intersection to ensure the conflict is identified correctly (Ibrahim et al., 2019). Proximity motion sensors are another way of tracking near misses. A study by Karakaya et al. (2023) uses a motion sensor as well as a gyroscope to automate the detection of near misses by using a model to dynamically calculate if a near miss occurred instead of using a fixed distance. This technique, however, can record uncommon maneuvers, such as a bicycle riding over a curb or raised surface as a near miss with a vehicle, and requires training the model to understand the differences.

Safety-based variables that can affect cycling route choice include the number of near misses and collisions, the cyclist's sightlines of infrastructure and other road users, the visibility of the cyclist to other road users and the number of passing vehicles and pedestrians. These variables are used in the thesis. The use of a model to identify near-misses is outside of the scope of this project, and the method of self-reporting near misses is sufficient enough to collect near-miss data while having minimal inaccuracy due to the data being from a very recent real-world experience. The data for the thesis are collected on a smaller scale (four routes in a neighbourhood). As a result, near miss and collision data are collected using manual identification via an on-bike video feed are conducted to confirm participants' self-reporting and to identify additional near misses.

2.4 Behavioural Route Attractiveness Variables

Behavioural variables depend on a person's knowledge, usage, and attitude toward an object or activity (Qualtrics, 2024). These variables are more challenging to measure quantitatively compared to infrastructure-based variables and are often measured qualitatively through survey questionnaires, with values assigned to quantify them (Petrisch, et al., 2007; Wu, Eaton, & Parente, 2020). For example, a survey conducted by Singleton (2019) used a 7-point rating scale to collect data on a cyclist's well-being where 1 represented a negative impact to their well-being and 7 represented a positive impact. Previous studies have considered behavioural variables that can affect cycling route choice. Compared to infrastructure-based variables, behavioural variables have been less commonly used in bikeability indices. Harkey (1998) considered comfort in their bikeability index, while Arellana et al. (2020) considered both comfort and the attractiveness of a route through its visual appeal and the cyclist's familiarity with the route. Some studies have been able to collect these variables purely quantitatively without the use of a survey. Other studies have included variables such as cycling well-being, range anxiety using ECCs, and the effect of fear on cycling usage (Singleton P. A., 2019; Divase, Devshete, Dhavale, Shinde, & Mahadik, 2019; Appleyard & Ferrell, 2017). Some studies include a combination of behavioural and infrastructure-based variables. One combination collects infrastructure data using instruments such as a GPS and behavioural data using survey responses while another combination can use a survey to collect responses and group cyclists into categories to evaluate their cycling performance (Krenn, Oja, &

Titze, 2015; Arellana, Saltarin, Larranage, Gonzalez, & Henap, 2020). The conditions of the infrastructure can strongly impact the decision to travel by cycling (Larranaga et al., 2016). This makes it essential to consider cyclists' preferences, comfort, and enjoyment when developing their ECC scores.

Comfort is defined as a satisfying experience when acting (Merriam-Webster, 2024). It can be affected by environmental, biological and psychological variables (Ayachi, Dorey, & Guastavino, 2015). A comfortable cycling experience is an essential component of choosing to cycle, especially for experienced cyclists (Sallis, et al., 2013; Fowler, Berrigan, & Pollack, 2017). Providing comfortable environments for cycling is challenging due to each individual’s different sensitivity to comfort in the same environment (Garrard, Handy, & Dill, 2012). However, research studies conducted over time have shown that general comfort is influenced by different types of urban infrastructure, such as:

1. Increases in urban vehicle and pedestrian traffic volume and speed are associated with lower comfort (Buehler & Dill, 2016; Epperson, 1994; Landis, Vattikuti, Brannick, & Level, 1997). A study by Krizek & Roland (2005) found from their regression model that the annual average daily traffic was the most statistically significant of the 30 explanatory variables tested in influencing the discomfort experienced by cyclists in the city of Minneapolis, USA.
2. An increase in lane width and spacing for the bike allows for an increase in comfort (Buehler & Dill, 2016). Landis et al. (1997) developed a BLOS using participant comfort and safety responses on a 6-point (A to F) scale. Their BLOS found that overall BLOS increased by 31% with the extension of a 3.7 m long painted bike lane to 4.9 m in the city of Tampa Bay, USA.
3. The type of urban cycling infrastructure influences the level of comfort depending on the separation granted by the infrastructure type from motor vehicles or pedestrians. Sharrows have the lowest comfort, whereas multi-use paths have the greatest comfort (Monsere, et al., 2014; Clark, Mokhtarian, Circella, & Watkins, 2021). Clark et al. (2021) found that the average comfort levels for participants increased when the cycling infrastructure type along a road was changed from sharrows to multi-use paths. Participants who were in favour of bikes had their comfort level increase from 3.6 out of 5 to 4.7 out of 5. Similarly,

participants who were in favour of cars also had their comfort level increase from 2.2 out of 5 to 3.7 out of 5.

Yet not all urban areas can provide the most comfortable cycling infrastructure for cyclists. Challenges arise for transportation decision-makers when tasked to provide comfortable cycling infrastructure. These challenges include capital costs associated with building and maintaining infrastructure, negative impacts on motor vehicle and pedestrian traffic and political opposition from stakeholders and other decision-makers (Dill, McNeil, Goddard, & Monsere, 2015; Harris, et al., 2013). A questionnaire conducted by Calvey et al. (2015) asked cyclists to identify the most important indicators they value when choosing a cycling route out of 24 possible options. The results showed that the comfort and pavement type, condition and roughness were more critical than the slope of the route and the presence of bicycle parking along the route. A cyclist's route preference can also be affected by the type and quality of the pavement surfaces along the route (Rybarcyk & Wu, 2010). The level of the vibrations experienced on these surfaces along the routes also reflects these route preferences (Giubilato & Petrone, 2012).

The level of vibration influences the ride comfort on a bicycle, with more vibration resulting in less comfort (Olmen, R, & M, 2012). Gao et al. (2018) created a Dynamic Cycling Comfort system to quantify cycling comfort on urban roads based on the perception of vibration. They found out that cyclists perceived the ride as comfortable when the average vibration acceleration (a_{wv}) is less than 1.62 m/s^2, moderately comfortable between 1.81 m/s^2 and 2.04 m/s^2 and uncomfortable when the average acceleration is more than 2.20 m/s^2. The pavement surface condition can also dictate the expected comfort of the route for the cyclist. Holzel (2012) collected data on standard adult bicycles on different pavement surfaces at different travel speeds. It was found that asphalt and concrete surfaces result in lower magnitudes of vibration acceleration compared to stone bricks, and gravel. Average speeds changing from 10 km/h to 20 km/h increased vibrations significantly on stone bricks compared to asphalt. On surfaces with cracked pavement, it was found that the increase in vibration was noticeable but still considerably less than on stone bricks. As a result, having routes with better condition asphalt or concrete pavement can result in cyclists choosing them to reduce the level of vibration that would be experienced, allowing for a more comfortable ride on a bicycle. The pavement surface condition allows cyclists to predict their experience on the route and allow them to determine alternate routes (Holzel, 2012).

For battery-powered electric vehicles (BEVs), the fear of running out of battery power for the electric pedal assist is another variable that cyclists would have to consider when choosing routes. This is known as range anxiety, which is the fear that the vehicle may not have sufficient battery or fuel capacity to reach a destination and would leave the vehicle stranded (Ulrich & Von Helmott, 2010). The majority of range-anxiety studies are associated with electric motor vehicles instead of electric bikes, but the behaviours experienced by drivers can also be experienced by cyclists, especially couriers, who are converting from fuel-powered vehicles to BEVs. Survey results analyzed by Yang et al. (2016) show that respondents' answers have a better goodness-of-fit with a pessimistic bias model than an optimistic bias model. This means that respondents have a defeatist attitude about the operating range with BEVs, which results in range anxiety affecting their route choice behaviour. In 2023, consumers were able to purchase BEVs with a maximum range of 400 km to 500 km on a single charge (Tchir, 2023). Tchir surveyed this event in 2022 and after this event in 2023 found that 44% of respondents were more likely to purchase a BEV which increased from 29% in 2022. As a result, the worries of range anxiety start to decrease as the BEV range improves. For last-mile or urban delivery, these services cover an average of 50 to 150 km per day, which existing BEVs, such as battery-powered delivery vans and trucks, can efficiently conduct. A 2023 survey conducted by the Ipsos research agency found that respondents' anxiety about BEVs was about the price first, charging access second and maintenance costs third, with range anxiety dropping to the fifth most worrying (Ipsos, 2023).

The concept applies to ECCs as well, but the use of the battery to assist conventional human-powered pedalling would mean that the cyclist would not be stranded as the vehicles can be pedalled or pushed to their destination. However, not having the electric pedal assist available can make it challenging for courier cyclists who are spending 8 hours per day delivering packages of various weights by cycling. This becomes a more noticeable factor in urban areas with routes on steep slopes. The estimated battery duration that is stated by manufacturers does not account for the payload weight, as this can vary with cargo density. Studies have estimated that an additional 50 kg of cargo can decrease the maximum battery life by 25% when riding exclusively on mostly flat terrain, while average slopes over 8% can decrease the maximum battery life by 70% (Savrum & Poyrazoglu, 2022; Divase, Devshete, Dhavale, Shinde, & Mahadik, 2019). This decrease in battery life can result in shorter routes, potentially fewer packages delivered by an ECC, or the failure to deliver to further destinations. ECCs tend to have shorter trip lengths due to the number of packages that can be carried by bike, but most commercially available ECCs tend to have an average range of 50 to 75 km on a single charge (Urban Freight Lab, 2020; Babboe, 2023; Tern, 2023; Mycle, 2023). As a result, range anxiety is becoming a less-important variable on various routes that are steep/hilly, long distances or delivery intensive for ECCs.

Battery life for ECCs also depends on the level of electric assist applied by the cyclist. ECCs often have an option that allows cyclists to change how much electric assist is applied when cycling. Cyclists who are more comfortable with the electric assist tend to increase the level to the maximum that the ECC can provide (De La Iglesia, et al., 2018). This increase in electric assist decreases battery range at the benefit of less pedalling of the ECC (Hughey, et al., 2022).

Cycling is beneficial to people as it can help improve their quality of life by ensuring physical and mental health is maintained (Cogara, 2012). Cycling is a non-weight-bearing form (less impact on joints) of exercise compared to running and can help enhance a person's social network while building confidence when conducted routinely (Oja, et al., 2011; Shephard, 2008; Matthews, et al., 2007; Hansson, Mattisson, Bjork, Ostergren, & Jakobsson, 2011). Some cycling surveys measured enjoyment and pleasantness (Singleton & Clifton, 2017). A study conducted by Zander et al. (2013) interviewed 20 participants in Sydney, Australia, before and after cycling for 2 hours per week for 12 weeks. All of the participants rated enjoyment as their primary motivator for cycling, with participants saying that it allows them to enjoy being outdoors and have a feeling of freedom that cycling offers. After the study, nine of the interviewers continued to cycle for their commute to work and daily routines.

Rissel et al. (2016) have found that focusing on enjoyment associated with cycling to work can help encourage more people to choose to cycle. Rissel et al. used the Sydney Transport and Health Study, which surveyed 675 participants about the amount of enjoyment received from their commute to work or study, along with their mode of transport, physical health, and demographic information. The enjoyment was adjusted based on the demographic information and data, such as the perception of their neighbourhood being more pleasant to travel to, as well as the feeling of being rushed. The results found that cyclists had a 52% enjoyment level over pedestrians at 46% and more than cars at 14% or public transit users at 10%.

A survey conducted by Singleton (2019) found that walking and cycling rated higher on measures of physical and mental health as well as overall well-being. Overall enjoyment was noticeably greater among walking and cycling compared to transit and motor vehicles, with enjoyment among cyclists having a higher score than walking. However, cyclists had higher ratings for fear and lower ratings for safety, resulting in cycling, in some cases, potentially being less enjoyable than walking due to the limited separation of cyclists and motor vehicles. The fear of traffic injuries can deter a cyclist or result in changes to their routes (Appleyard & Ferrell, 2017; Schneider, 2013) with the feeling of being less secure than in cars due to interactions with strangers or being victimized (Singleton & Wang, 2014). Singleton found that people are captivated by a particular mode or transit solution based on the efforts to improve it, which increases the enjoyment of that mode. This can also apply to cycling route choice, where efforts to improve certain roads and paths to improve the cycling experience can increase cyclist usage of those routes as they lower the fear and increase the safety and enjoyment of cyclists.

Behavioural variables that can affect cycling route choice include comfort, enjoyment and range anxiety. The comfort can affect the cyclist's route choice through poor quality infrastructure and physical and mental discomfort while using the ECC. Enjoyment can affect a cyclist's route choice through the amount of motivation and fear that the cyclist experiences. It can also influence the use of ECCs as an alternative mode for work, shopping and commuter purposes. Range anxiety behaviorally affects how far the cyclist can travel on an ECC before wanting to recharge the battery. This thesis considers comfort and enjoyment as behavioural variables. Pavement condition is also considered but depends on the comfort experienced. Range anxiety is omitted due to the long range of ECCs, and the short distance routes used for participants which would result in range *anxiety not experienced during the field survey.*

2.5 Bikeability Indices and Analytical Hierarchy Process

Existing bikeability indices are looked at to develop a routing model for ECCs. Bikeability indices were created to make it easier for people to determine if a location is suitable for cycling trips. The Bike Score© developed by Redfin is the most commonly used bikeability index service in real estate (Walk Score, 2023). The Bike Score© uses components that can be applied to commercial ECCs, particularly destination accessibility by cycling and the presence of bike lanes. It uses a 0-100 score based on four equally weighted components applied to neighbourhoods.

1. Bike Lanes close to the location.
2. The topography of the location.

3. Access to destinations from the location by cycling via travel distance (block length) and intersection density.
4. Access to bike-sharing services from the location.

Another score used to rank bike routes is the Canadian Bikeway Comfort and Safety Classification System. The classification system ranks bikeways on a low-medium-high comfort scale that considers variables such as transportation connectivity, real-world access to amenities, infrastructure, vegetation, travel distance and travel time (Aluning, Clement-Godbout, & Vietinghoff, 2024). Comfort is classified as the inverse of traffic stress, with high comfort bikeways having low traffic stress and low comfort bikeways having high-traffic stress. The score makes assumptions such as the use of a road bike, willingness to use hills, complete streets, and avoid bad surfaces, and the cyclist can travel 18 km/h on average. The system considers spatial accessibility as the sole contributor to comfort but does not explicitly consider other variables that may influence the cyclist's physical or behavioural comfort when using a particular bikeway. The system uses satellite imagery and tagging through crowdsourced Open Street Maps data but does not take into consideration the geometric design of the infrastructure along the route, which has resulted in gaps and inconsistencies in their dataset (El-Fateh, et al., 2024).

The Highway Capacity Manual includes a Bicycle Level of Service (BLOS) which evaluates the performance of road segments, intersections and multi-use paths using a rating scale from A to F (Transportation Research Board, 2017). A BLOS of A indicates that conditions are optimal to accommodate additional cyclists whereas a BLOS of F means that the route is crowded, and cyclists are more likely to come into conflict with each other. The variables used to compute the BLOS are primarily infrastructure-based variables. The BLOS for road segments considers the bicycle midsegment speed, delay from the intersections and the travel speed. The BLOS for intersections considers the capacity of the cycling lane, the intersection delay, lane width, vehicle flow rate and the presence of on-street parking. The BLOS for shared paths considers the hourly demand of the mode, the average speed of the mode of travel on the path mode split, encounters between traffic in the opposite direction, active and delayed passing, and the number of effective travel lanes. For low-volume paths, the BLOS is assumed based on the number of passings and meeting events to score the path as a BLOS of A or B. The BLOS is a tool used to evaluate the performance of individual road segments, intersections and paths. It can provide valuable insight to transportation planners and engineers to improve the performance of road and cycling infrastructure to reduce travel congestion. However, it is not the best tool to be used to identify routes for ECCs as each BLOS for the intersections, segments and paths are for individual locations.

A bikeability index often combines variables to create an index with a weighted distribution based on the importance of the variable to cycling route choice (Hall & Richard, 2010; Frank, Schmid, & Sallis, 2005; Emery, Crump, & Bors, 2003). A bikeability index developed by Harkey (1998) weighted nine different cycling variables related to route preference. The model indexed road segments using variables including the presence and size of cycling infrastructure, posted speed limit, cycling parking facilities, land use and traffic volume. It uses adjustment factors that scale the desirability based on the truck volume, right-turning volume and parking time limits. These adjustment factors scale based on perceived comfort for the cyclists. Higher hourly truck volume and lower time between truck and bike interactions indicate a poorer route. A stated preference survey involving cyclists shows results varied between the type of cyclist and urban areas.

A bikeability index was developed by Van Dyck et al. (2012) based on built environment variables such as proximity to destinations, access to walking or cycling facilities, and ease of finding bike parking near shopping areas. The index showed that there were consistent relationships among the countries assessed, including the United States, Australia, and Belgium, in the survey and that no gender or country-specific differences affected the score. Rybarcyk & Wu (2010) developed a bikeability index incorporating the pavement surface condition using the Federal Highway Administration's 5-point surface condition rating system, where 5 is the best condition. The condition rating system is based on the remaining functional period (RFP) and the remaining structural period (RSP) values (Federal Highway Administration, 2017). The RFP is the shortest time (in years) from the last data collection to when distress reaches a functional threshold, based on ride quality and skid resistance. This threshold is when a defect in the pavement occurs that affects the ride quality and safety of road users. The RSP is the shortest time (in years) from the last data collection to when distress reaches a structural threshold. This threshold is when underlying damage in the pavement will cause it to fail. The index was developed using variables like traffic volume and lane width.

Winters et al. (2013) incorporated GIS data on urban infrastructure features and conditions together with survey results to develop a bikeability index that identifies areas where cycling is poorer and where cycling is better in the city of Vancouver, Canada. The survey found that bicycle facilities, topography, traffic, trip distance and relative travel speed strongly influence the cyclists' routes. The index considered a summation of the following five variables multiplied by their weighting: cycling route density, route separation, connectivity to cycle-friendly streets, topography, and destination density. The scoring components were scored on a 10-point scale, with 10 indicating the most bikeable areas. The weightings were obtained from an opinion survey and a focus group interview. The weightings were visualized using ArcGIS software and represented routes within a 10 m wide and 10 m long cell within the study area.

A similar index was developed by Krenn et al. (2015) and considered the area of available green and aquatic spaces in addition to the variables considered by Winters et al. (2013). The variables adapted include a binary indicator of cycling infrastructure, the total length of the cycling infrastructure along a route and the distance between two cycling infrastructure segments on a route when the route has to use roads without cycling infrastructure. Krenn mentions that a strength of their bikeability index is that it reduces the inputs to a small set of the most important variables influencing cycling route choice. This allows the index to be used to create bikeability indices for other routes and can be scaled to use in geographically larger or smaller areas.

Having a high bikeability index score along a route can lead to more cyclists using that route instead of other transport modes, thus continually increasing the bike-friendliness of the area (Hardinghaus et al., 2021). A low bikeability index score suggests that the route is a less desirable choice. Arellana et al. (2020) developed a bikeability index for the city of Barranquilla, Columbia and found that the routes with a low index are also the same routes with the highest rates of vehicle-associated collisions. The survey responses that were used to develop the index showed that having a secure route was the most critical variable for those that cycle as their primary mode of transport.

The variables and methods used in bikeability indices from the previous sections are summarised in Table 1. The table is not a comprehensive list of the different bikeability indices that exist but represents a sample of different indices and how the variables and the methods over time have largely remained consistent. This includes methods such as using surveys and geographical data as well as using a regression model. The variables collected through these methods are primarily infrastructure and sociodemographic with some inclusions of safety and comfort used in more recent indices. Variables that are expected to have a minor effect are not collected in the thesis. Variables demonstrating a major effect in the bikeability indices are considered in the ECC score. Preference is given to variables that are easy to measure and can be collected through surveys or objective data collection instruments. There has not been an ECC scoring system that focuses solely on ECCs, as existing scores have focused only on conventional bikes and E-Bikes.

Table 1: A Sample of Bikeability Indices from Literature.

Reference	Data Collection Methods	Index Methods	Input Variables
Harkey (1998)	Stated Preference survey and Video survey	Regression model using weighted variables	Lane width, Traffic speed, Traffic Volume, Overall comfort
Van Dyck et al., (2012)	Revealed Preference survey, GIS data including walkability index and four land use variables	Generalized additive mixed models with negative binomial variance	Neighbourhood built environment (destinations, land use, traffic safety, walk and bike facilities, connectivity), social, environmental, physical activity, socio-demographic
Winters et al. (2013)	Stated Preference survey, Travel Behaviour survey, and Focus Groups	Regression model using weighted variables	Cycling infrastructure preference, cycling parking facilities, destination connectivity, topography, land use
Kreen et al. (2015)	Revealed Preference surveys with GPS logging	Regression model using weighted variables	Cycling infrastructure, presence of pathways, presence of roads without bike lanes, green and aquatic areas, topography
Arellana et al., (2020)	Stated Preference surveys and focus groups	Discrete choice model using probabilities that represent the weight	Directness and Coherence, comfort and attractiveness, traffic safety, security, climate, cycling infrastructure presence, trip cost

Bikeability indices are formed using scoring techniques which take the data input and weigh the importance of the variable type compared to other variables. A higher weight indicates a more significant impact on the index, while a lower weight indicates a less significant impact on the index. Harkley's (1998) index weighted variables using a relationship between bike-friendliness in the neighbourhood and the number of cyclists. Winters (2013) weighted their variables using a relationship between the level of discomfort and the 85th percentile speed. Kreen (2015) weighted their variables using weightings developed from survey focus groups to build the index. Van Dyck (2012) used discrete choice models using the probability of the utility to weigh the variables.

Arellana (2020) developed mathematical models to estimate the effect of the attributes on one another.

Another technique of determining the weightings to develop a scoring index is known as the analytical hierarchy process (AHP). The technique is used for group decision-making in a wide variety of stakeholder-based decision-making situations ranging from government to industry to business (Peniwati, 2017; Satacoglu, 2013). AHP aims to find the decisions that are best suited for an established goal among a range of criteria evaluated between a set of alternatives. This is done by conducting pairwise comparisons. An example using Figure 1 with a hypothetical goal is to choose the most suitable leader. There are three hypothetical alternatives to choose from, namely, Tom, Dick, and Harry. These alternatives have different criteria options consisting of experience, education, charisma, and age. The criteria are compared with each other to calculate weights that identify how comparatively important they are in choosing the most suitable leader. Then, the criteria are compared among the three alternatives, and the outcome is the person with the highest weighted result.

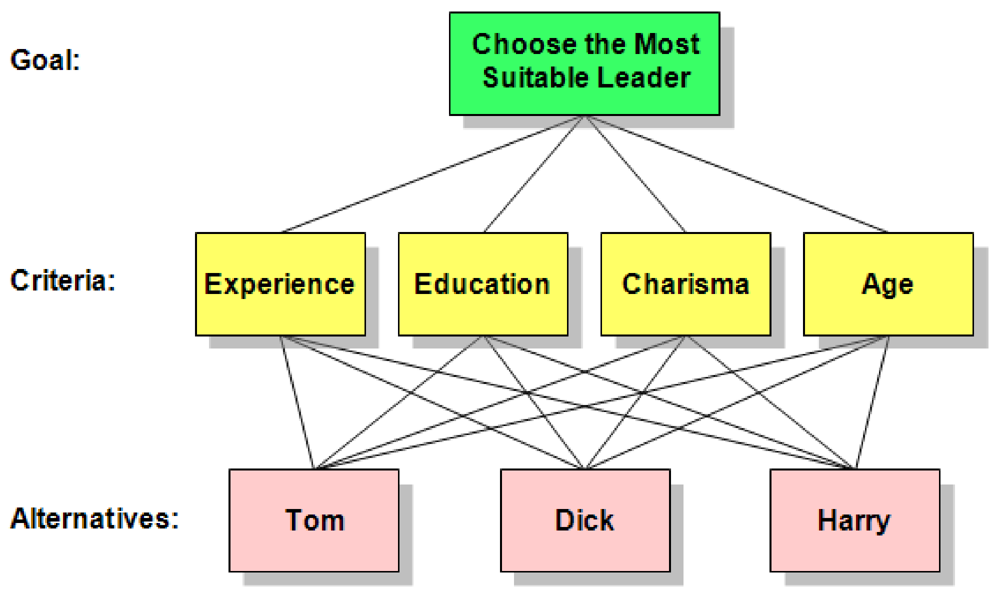


Figure 1: Analytical Hierarchy Process Example
Adapted from source: (Sander, 2010).

Each item within a level is designated as a node. The criteria nodes are compared with each other based on how important they are for the goal. Then, the alternative with the higher of that criterion is weighed in favour of the goal. For example, if experience is more critical for the most suitable leader than the other three criteria, then if Harry had the most experience, the decision to choose the leader would weigh in favour of Harry. Pairwise comparison questions are given to stakeholders according to the AHP fundamental scale to calculate the weights. The scale is from 1 to 9, with 1 being of equal importance among the pair of nodes and 9 being of extreme importance among the pair of nodes (Saaty T. L., 1980). For example, if experience is extremely important compared to education, then a value of nine would be assigned to experience. AHP has rarely been used in cycling-related research but is commonly used in decision-making in transportation planning and management (Piantanakulchai & Saengkhao, 2003; Sivilevičius & Maskeliūnaite, 2010; Mahmoud & Hine, 2013).

AHP has a limitation where the greater the number of variables (criteria) that are evaluated, the more complex the pairwise matrices are for comparison (Ignaccolo & Nemery, 2013). Collecting the preference data among stakeholders for each variable would take longer, requiring a longer survey completion time, which can detract potential stakeholder participants. One way to accommodate this is to take a possible list of variables and compare them with similar literature, filtering the most important variables to evaluate within the survey to conduct AHP while removing the lesser important variables (Ignaccolo, et al., 2017). Also, to mitigate the effect of an individual's judgements, a consistency check can be performed to ensure that each individual's responses are consistent among the matrix elements, with more than 90% consistency being acceptable (Saaty T. L., 1980).

The weightings for the AHP can be computed using two pairwise comparison methods: the eigenvector method and the geometric mean method. The eigenvector method derives the priorities or weightings as solutions of the eigenvalue obtained from the comparison matrix (Saaty T. L., 1980). The priority values are determined through an eigenvalue-eigenvector decomposition of the matrix using the normalized eigenvector associated with the largest eigenvalue of the matrix. For matrices that have high inconsistencies, when transposing the matrix, the solution no longer becomes reciprocal of the original matrix's solution, which can cause difficulties in interpreting the priority values (Johnson, Beine, & Wang, 1979). The geometric mean method uses a normalization factor to derive the priorities, which are used to estimate and rank the matrices (Crawford & Williams, 1985; Kumar & Ganesh, 1996). A study by Budescu et al. (1986) found that the geometric mean method is more straightforward to calculate compared to the eigenvector method, but both were able to give similar priority values for consistent matrices. The geometric mean method maintains the reciprocal when the matrix is transposed, and the values obtained are the maximum likelihood estimates of the priority values, which allows it to be used for matrices with higher inconsistencies (Williams & Crawford, 1980).

One limitation of both techniques is that if the responses in the pairwise matrices are not perfectly consistent, then errors can occur, which results in the information being less reliable in ranking the elements (Tomashevskii, 2015). However, minor errors such as the consistency ratio being less than or equal to 0.1 are allowed, which enables a reliable ranking to be obtained from the matrices (Saaty J., 1977) Muralidharan et al. (2003) found that for results with consistency ratios between 0.1 and 0.2, the results can be used if the confidence level of all results falls within 90% or greater. The eigenvector method is more sensitive to changes in the pairwise matrices compared to the geometric mean, which leads to higher standard deviation or variance in the weightings (Mazurek et al., 2021).

AHP produces a pairwise comparison matrix for each participant's response to the problem. The responses need to be aggregated together so that the weightings are reflective of the entire sample surveyed. For AHP, there are two standard aggregation methods: aggregation of individual priorities and aggregation of individual judgements (Forman & Peniwati, 1998). Individual priorities compute the arithmetic mean from each respondent's calculated weights. Individual judgements combine each respondent's comparisons as a weighted geometric mean with the final matrix calculated using the approximate eigenvector methods to compute the final weights. Individual priorities are best when the group is assumed to act as individuals, such as political stakeholders deciding on an issue such as welfare, whereas individual judgement is best when the group is assumed to act as a whole, such as when determining corporate or public policy directions.

For the thesis, the AHP is used to determine the weightings for the ECC score of each route tested to decide the best cycling route for ECCs. The method allows for qualitative and quantitative variables to be weighted using the judgements (responses) of each participant. The method can determine the variables with the highest weights based on the judgements of the participant pool and can check if the outputs are consistent with each individual's responses. Chapter 4, Section 4.2, ECC Score, explains how the AHP is applied among the data collected to compute the weightings for the ECC Score for each route. The geometric mean method is used to weigh the AHP results due to its lower variance and its ability to produce values that can be interpreted correctly when the matrix has higher inconsistencies. The individual judgement method is used to aggregate the respondent's matrices because we want to develop a weighted ECC score that can be applied without significant influence from certain groups of participants.

2.6 Cycling Route Choice Surveys

The two most commonly used types of surveys in cycling route choice are stated preference (SP) and revealed preference (RP). RP cycling surveys collect data from respondents based on previously experienced cycling trips. RP surveys related to cycling route choice have been conducted in studies such as Shah & Cherry (2021), Rupi et al. (2023), Lachapelle et al. (2021), and Guo et al. (2017). These types of surveys are limited to real-world observation data, which may contain an insufficient number of variables or low variation, which can lead to the variables lacking sufficient representation and low correlation (Train K. , 2002). RP surveys are based on previous observations of real-world events that may not be correctly recalled by the respondent, leading to potential inaccuracies in the collected data. RP survey data cannot be used to evaluate a new policy or recently adopted mode of transportation, such as ECCs, due to a lack of familiarity and sample size. However, these inaccuracies can be minimized if the experience is very recent.

SP cycling surveys collect data based on the preferences of respondents when faced with recently experienced real-world or hypothetical scenarios of route options and characteristics (Green & Srinivasan, 1978). This includes surveys where cyclists test-ride as part of the study to record the respondent’s recent experience. SP surveys related to cycling route choice have been conducted in studies such as Winters et al. (2013), Arellana et al. (2020) and Guo et al. (2017). SP also allows for the collection of observational data due to its real-time experiences, such as video capture of a cyclist’s experience when riding the route (Kroes & Sheldon, 1988). Capturing this data allows a limitation of SP to be addressed. This limitation is due to the potential for inherent bias (policy bias or justification bias) or inaccuracy from the respondents in the collected data, as they may not choose the option when faced with the scenario in reality (Ben-Akiva & Morikawa, 1990). This usually occurs when respondents are unable to understand the scenarios. However, since SP allows observational data, allowing participants to experience the mode for some time can mitigate potential bias and inaccuracy of responses.

Another limitation of SP surveys is the duration of the study. Asking a large number of questions can lead to respondent fatigue and a higher risk of inaccurate responses (Lin, Srikukenthiran, Miller, & Shalaby, 2018). In the context of cycling surveys, exhaustion from responding to a large number of questions or from cycling on too physically demanding routes can lead to respondent fatigue. This results in the data having to be removed from the study, decreasing the sample size to maintain accurate responses within the dataset.

A survey requires accurate survey design and administration. This includes variables that realistically affect ECCs in a chosen study area and extensive data collection from the survey. Furthermore, surveys that focus on the variables influencing cycling route choices have found that access to cycling facilities and hilliness are of lower importance among cyclists in choosing their cycling routes compared to other variables, such as a direct route to reduce travel time and comfort which is considered more critical among cyclists (Winters et al., 2011; Calvey et al., 2015; Guo et al., 2017). For the SP survey, it is ideal to have a physical presence for the interview due to the higher response rate as well as maintaining contact up until the completion of the survey (Kawamura, 2000; Zhou, Burris, Baker, & Geiselbrecht, 2009). For a survey that involves respondents riding an ECC, the survey has to be completed after the ride to develop results based on their experience and minimize bias due to inexperience in the transportation mode. Since the survey involves both a test ride and an interview, the time spent by the participant on the survey should be minimized to prevent survey fatigue from appearing in the responses. To prevent this, the number of scenarios would have to be minimized to balance the number of responses while still being able to record all effects of the variables measured. The related studies had a range of 7 to 10 variables (Lin, Srikukenthiran, Miller, & Shalaby, 2018; Winters, Brauer, Setton, & Teschke, 2013; Arellana, Saltarin, Larranage, Gonzalez, & Henap, 2020; Guo, Zhou, Wu, & Li, 2017). The study conducted by Lin et al. (2018) narrowed down the survey to 10 variables. The survey developed by Winters et al. (2013) focused on cycling infrastructure and had eight variables, while Arellana et al. (2020) had seven variables, and Guo et al. (2017) had eight variables.

Monetary and non-monetary incentivization tools can be utilized to ensure respondents are engaged through the ride and survey (Ben-Akiva, et al., 2016). Survey incentive tools include an instant payout which can be in the form of a gift certificate or an item with a monetary value associated with it, a points-based system that grants points for each component of the survey that is completed that can be redeemed for rewards and raffle entries into a random prize draw for an item of a high monetary value (Qualtrics, 2024). These tools have limitations such as no guaranteed reward for raffle entries, participants rushing through completing the survey or not completing the survey correctly due to only wanting the incentive. While financial incentives can increase respondent participation and maintain engagement during longer surveys, data accuracy may be compromised depending on the amount of harm that the incentive would cause to the survey results. While providing a high-value incentive can increase participant turnout, it can also attract more participants who care less about the purpose of the survey (Singer & Couper, 2008). This can result in responses to questions to be inconsistent with other responses in the same survey as the participants

Cycling studies sometimes use the entire city for their study area when focusing on infrastructure to account for a wider variety of infrastructure types that can be experienced, as well as using routes that converge in high-interest destinations from other parts of the city. Safety-focused cycling studies tend to focus on certain mixed-traffic intersections, such as where truck and cycling traffic is high or in downtown areas where cyclists interact more closely with cars and pedestrians. Studies that focus on visibility of cyclists and sightlines tend to include regions with either dense buildings, poor signage, giant billboards or dense vegetation that can obscure road and sidewalk users.

Previous cycling surveys tend to have similar themes and structures. Many surveys included general demographic questions such as age, gender, and city of residence, with questions related to bike usage, previous experience and travel patterns. Surveys tended to ask participants to either rank or prioritize a list of infrastructure or safety-based variables (Winters et al., 2013). Some surveys ranked observable variables such as infrastructure quality and traffic flow, and non-observable variables such as comfort and path attractiveness (Arellana et al., 2020). Some surveys included open-ended responses, which tend to discuss collision history as well as their experience interacting with the built environment on the bicycle (Howard & Burns, 2001; Lachapelle, Carpentier-Laberge, Cloutier, & Ranger, 2021). Route ranking was rarely included among the survey questions due to the studies prioritizing variable ranking to develop bikeability index weightings or to explain the importance of a variable in cycling.

The number of participants can affect the sample size of the survey. Having a larger sample size can improve the accuracy of the average data values collected while providing smaller margins of error. It also allows for the elimination of participant studies that do not show any engagement or have conflicting responses to be removed from the sample without significantly increasing the margin of error. Qualitative field research typically uses smaller sample sizes than quantitative field research due to text-based and open-ended answers being more challenging to analyze (Mahmutovic, 2022). Previous studies of cycling route choice involved collecting data through mixed-field surveys. Previous cycling surveys had between 140 and 160 participants (Howard & Burns, 2001; Hardinghaus, Nieland, Lehne, & Weschke, 2021; Broach, Dill, & Gliebe, 2012). The participants were selected using non-probability methods via volunteer sampling among commuter cyclists within their respective cities. This allows for surveys to be launched, executed, and finished in shorter times while reducing respondent burden (Statistics Canada, 2021). Meanwhile, studies such as Winters et al., (2013), Calvey (2015) and Lachapelle et al. (2021) sampled 72, 75 and 34 cyclists, respectively. Winters et al., (2013) split the pool into four different groups based on their cycling frequency. Calvey (2015) recruited cyclists using word of mouth, email, and poster flyers targeting cyclists at a university campus, and it accepted those with sufficient cycling ability to participate. A further 20 of the 75 sampled were sampled due to their experience in off-road cycling and their expertise, allowing them to discern more minor details in changes to the cycling environment. LaChapelle et al., (2021) study specifically targeted commercial cargo cyclists due to their reliance on cycling as part of their work rather than as part of their commute, allowing for a more accurate representation of cargo cyclists in the sample. However, this sampling method makes it challenging to assess the quality or sampling error of the sample and may result in noncoverage or under-coverage bias since only people who are familiar with riding a conventional bicycle or cargo trike are accepted to partake in the study (Statistics Canada, 2021).

Previous cycling surveys were conducted as self-administered questionnaires or interviews from conducting rides in a study area. A self-administered survey questionnaire conducted by Howard & Burns (2001) in the city of Phoenix, USA, looked at the influence of near misses and their effect on a cyclist's perception of a safe cycling route as well as how it affected route choice decisions. They surveyed 140 cyclists collecting demographic data (age, gender, residence, vehicle ownership), safety data (accident involvement, helmet usage) and route preference and safety perception of the route. The survey was split into two parts: The first was a combination of ranking questions on a scale of 1 to 5 regarding cyclists' commute to work, and the second survey was a series of open-ended questions describing the route they used to commute. The survey was distributed via advertisements in local publications, bike shops and bicycle-related meetings and events. The survey was used as input to develop a series of routes using GIS tools to analyze the spatial and infrastructure variables that resulted in cyclists choosing specific routes.

Singleton (2019) surveyed 700 commuters through a 30-minute-long questionnaire to understand commuters' well-being by measuring different travel effects (distress, fear, attentiveness, enjoyment, safety). Participants would rate their most recent cycling commute trip to work on a seven-point scale with options consisting of statements such as happy and sad. The survey was distributed online and was used as an input to measure the effect of subjective variables on cycling travel.

Winters et al. (2013) conducted an opinion survey and a focus group interview to collect data to develop a bikeability index based on infrastructure, traffic, and environmental variables. The survey was administered online to 1402 active and potential cyclists from Vancouver, Canada. 66% of the questions were about potential motivators and deterrents to cycling, while 33% of the questions were related to the built environment. Participants ranked the variables in order of importance where rank 1 was assigned 3 points, rank 2 was assigned 2 points and rank 3 was assigned 1 point. This was added among all participants who had ranked the variable in their top 3 choices. The focus group interview was conducted to provide context on how the built environment contributes to making an area bikeable. Variables that could be undertaken in the scope of municipal legislation, such as zoning and urban planning, were emphasized to the groups. Four groups of 8 to 10 participants were included, based on three groups from the survey respondents and a fourth group from cycling advocacy communities.

Since ECCs are an emerging mode of transportation, likely, the participants may not have used an ECC or a trike-style variant E-Bike previously. Also, all of the participants are riding on the ECC for an extended duration, they can accurately recall their experience using it because the survey is immediately after the ride. As a result, the survey is both RP and SP due to the unfamiliarity of the ECC mode among participants, as well as the ability to collect observational data while minimizing inaccuracies from participants recounting their experiences. The survey considers 9 variables from the literature to balance the effect of survey fatigue while allowing for a sufficient amount of data to be collected to develop the weights. The study has a monetary incentive, but measures are taken to prevent data exposure, allowing for accurate data to be given by the respondents.

The minimum sample size needed for the study can be derived from the Central Limit Theorem. It is a statistical theory that is used in many different fields to make inferences about population parameters when the population distribution is unknown (Turney, 2022). It is used in the thesis to estimate from a sample of ECC users the variable weightings for the larger ECC population. This theorem states that the sampling distribution of an average will approximate a normal distribution regardless of the population's actual distribution pattern as long as the sample size is sufficiently large (Boston University School of Public Health, 2024). This theorem has guidelines which require a minimum of 30 data observations for the theorem to hold (Emory University, 2024; Mascha & Vetter, 2018). However, a variable with high variance requiring a small confidence interval will require more sample observations. In addition, the sampling technique needs to involve random sampling of participants so that there is no bias in the results and that the sample should be as large as possible to get closer to the normal distribution. All respondents will be surveyed using the same set of questions with a minimum target of 30 participants. This will ensure the sampling technique aligns with the requirements to uphold the central limit theorem.

2.7 Route Choice Modelling Techniques

Route choice models aim to forecast a traveller's behaviour under different scenarios to understand their reactions and predict future traffic conditions on routes in the transportation network (Prato, 2009). Different techniques exist to create a dataset of alternative routes based on desired preferences, such as shortest path duration or shortest route length. Link labelling is an approach that takes in a large set of physical routes and converts the links into a smaller set of paths tagged with a label indicating their characteristics (Moshe et al., 1984). The labelled paths can determine an optimal path based on a set of parameters that can be analyzed from their characteristics. The labelling approach takes advantage of multiple link attributes, such as travel time and travel distance, to produce functions to minimize or maximize attributes to create alternative routes (Ben-Akiva et al., 1984). Link elimination is another technique which performs an iterative search of the shortest path by removing the shortest path link from the previous iteration to determine new optimal routes (Azevedo et al., 1993). The link penalty method is similar to link elimination, except it incorporates a penalty factor for using a link that from a previous iteration was selected as part of the previous shortest route. The factor can also be applied to specific characteristics to quantify the quality of the path, such as pavement conditions (De La Barra et al., 1993). The fourth method, simulation, produces alternative paths by creating impedances on the links following a random probability distribution (Prato & Bekhor, 2006).

Previous studies of modelling route choice for bicycle route preferences looked at comparing different route choice methods that aimed to model the shortest path with accuracy similar to the observed shortest paths (Bekhor, Ben-Akiva, & Ramming, 2006; Broach, Gliebe, & Dill, 2010). Broach et al. (2012) looked at 164 commuter cyclist route preferences in Portland, United States, to develop a labelling algorithm that identified the maximum potential of a given cycling route relative to variables such as urban infrastructure, type of bicycle and slope. A survey was conducted during the ride that collected data such as cyclist demographics, cycling travel patterns and travel behaviour with GPS, weather and trip purpose data. Three techniques were experimented with K-shortest paths, simulation, and route labelling. Route labelling was able to produce behaviorally realistic paths by maximizing or minimizing specific route criteria (paths that did not leave and return to the same corridor multiple times), whereas the other techniques produced behaviorally unrealistic paths. Skov-Peterson et al. (2018) used link labelling to generate feasible route alternatives from route preference data matched with GPS data for 1267 trips. It was found that the technique predicted over 80% of the routes in which the expected route choice was identical to the observed route choice. Alivand & Hochmair (2015) developed a route choice model that used the labelling technique combined with a link cost computed using the travel time to determine the shortest routes (lowest link cost). The duo collected GPS, route, and geographic information (travel diaries and geotagged photos) data to develop the model. The use of labelling within the model generated highly consistent results relative to the link penalty and link elimination methods that were also tested.

A data-driven approach to route choice modelling by Ton et al. (2018) evaluated the link elimination and link labelling on bicycle route choice data. The study collected demographics, road network, cycling facility, trip (time and distance) and GPS data within the city of Amsterdam, Netherlands. The model results showed that the labelling approach had a more diverse choice set than link elimination, which can mimic the observed behaviour better due to the number of different route options, allowing for better reproduction of the observed routes. The routes produced from labelling are spatially distinct and follow the direction of the traffic within the road network. However, due to optimizing for each variable, the standard deviations tend to be more significant for the routes compared to elimination.

Route choice modelling has its limitations. The first is the physical overlap among routes (Prato, 2009). The overlap problem occurs when several alternative routes overlap with near-identical paths. The overlap problem is important to address when routes are generated from the model and not from preset routes. Route choice models can also exhibit a decrease in a path's utility as the number of overlapping routes increases (Cascetta & Papola, 2001; Ben-Akiva & Bierlaire, 1999). This is due to a correction term known as a commonality factor being introduced in the model, which reduces utility depending on how similar the route is to other routes (Prato, 2009). Utility reduction does not occur in some correlations when the degree of correlation among the alternatives is comparable (Hoogendoorn-Lanser et al., 2005).

One method of route choice is an ordered logit model. An ordered logit is used for variables that have an ordinal scale of measurement, such as a 9-point scale from 1 to 9 (McCullagh, 1980). It allows for more than two ordered response options to be used as inputs. The model can overcome the main challenges that other logit models face, such as taste variation and the independence of irrelevant alternatives while allowing for ordered rankings as inputs compared to binary variables (Train K. , 2009).

A limitation of the ordered logit model is the use of a single utility function. This can result in the loss of information because the model may not capture all of the differences within the dataset (Willams, 2016). This is more prevalent if the relationship between variables is different across categories. The model assumes that the relationship between each pair of outcome groups is the same (Williams R. , 2022). If this is not satisfied, the model may not be an accurate reflection of the data. A single utility function may also result in the model being more challenging to interpret to predict outcomes (Willams, 2016). The use of a single utility function may make the model overly restrictive because of the assumption of using constant thresholds (Winkelmann & Boes, 2005). This can limit its flexibility to estimate the effect that prediction-based variables would have on the probabilities.

This thesis uses preset routes so overlap would not occur. An ordered logit model is identified as the preferred technique to analyze the data to identify participants' preferences in ECC route choice because the study uses a survey to collect perception data using rating scales from 0 to 10. The purpose of using the ordered logit model for the thesis is to identify the most statistically significant variables to retain in the ECC score.

2.8 Research Gaps

Despite extensive research surrounding bikeability indices and ECCs, there are significant gaps in the literature. First, in North American cities, ECCs are still being piloted so there are limited data sources that can be used to develop a bikeability index. Most of the studies using ECCs had to collect their data through surveys and test rides. As previously seen in permanent ECC programs in European cities, some courier companies have adopted ECCs, and many cities have implemented policies to increase their adoption.

Second, very few cycling studies and bikeability indices use behavioural variables in their analysis in combination with infrastructure and safety-based variables. This is due to challenges in quantifying behavioural variables (Harkey, 1998; Arellana et al., 2020). Third, existing bikeability indices were designed for conventional bicycles and do not consider the ECCs cargo capacity, electric assist and three-wheeled configuration which can result in different results. These characteristics can noticeably change how the cyclist rides and makes route decisions to improve their experience.

Fourth, while multi-criteria decision-making processes such as AHP are used in many different research fields including transportation planning, they have rarely been used in cycling-related research. While the use of dummy variables to represent qualitative results can be used for simpler forms of qualitative data such as gender and age, for more open-ended data such as the different reasons for not cycling on a route, a loss of information can occur. This is because the dummy variable would have to condense multiple combinations of responses into a few variables. AHP can consider both types of variables using pairwise comparisons which accounts for qualitative judgements without the loss of information because the qualitative data does not need to be converted into a dummy variable. The indices are also not standardized which makes it challenging for the index to be used by other decision-makers using their data inputs as different scenarios can generate unrealistic results such as routes that have low travel times but high travel distances having the same score as a route with a moderate travel time and distance.

Chapter Three: Data

3.1 Study Area

<u>3.1.1 Overview of Routes</u>

The study area is located within the York University Keele Campus in Toronto, Canada. A fixed origin and destination point are chosen to include the Bergeron Centre at 11 Arboretum Lane and 190 Albany Road as shown in Figure 2. These locations are selected to create routes with different cycling infrastructures and conditions while ensuring that participants can complete all four routes within the allotted time. It is expected that participants complete the entire session within an hour with an expected time of 8 minutes to complete each route. The use of four routes allows for a better understanding of cyclist behaviour in certain conditions as well as how their comfort changes across different routes. The study area includes major destinations with various types of cycling infrastructure, multiple traffic modes including cars, trucks, buses, bikes, pedestrians and micro-mobility vehicles, and events that can obscure road users and cyclists, such as transit buses making stops on single-lane roads and delivery vehicles loading and unloading in cycling lanes.

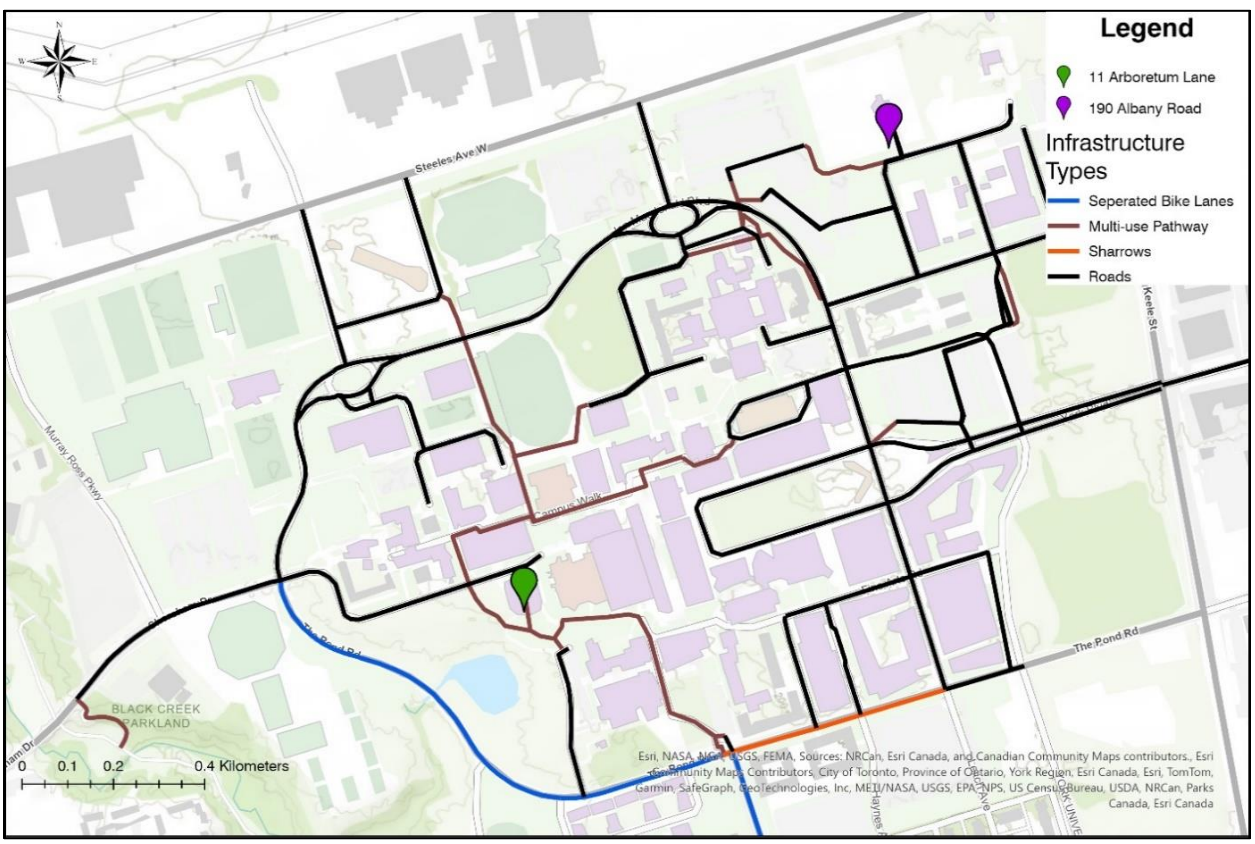
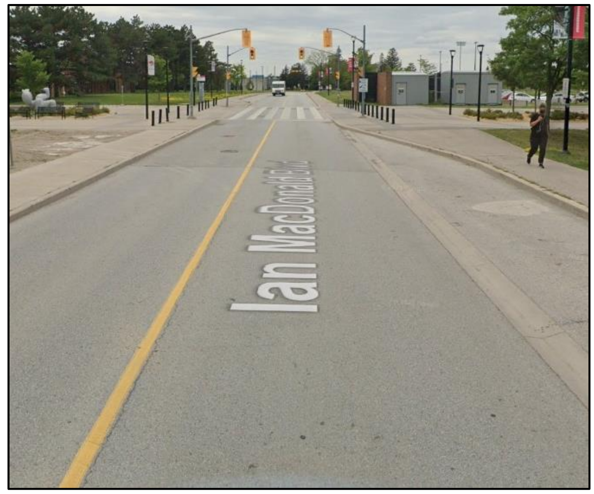


Figure 2: Bike Infrastructure within the Study Area

The study area features different types of cycling infrastructure: Sharrows, painted bike lanes and multi-use paths. Sharrows or shared lane markings are a type of cycling infrastructure on streets with a painted double chevron with a bicycle symbol on the right side of the curb lane (San Francisco Municipal Transportation Agency, 2016). This encourages cyclists to use the marked portion of the lane to travel on while assisting them in positioning themselves between either a moving vehicle or on-street parking (US Federal Highway Administration, 2009). Painted bike lanes are marked bike lanes with a painted separation marking to prevent motor vehicles from entering the space or blocking the lane (Deegan, 2018). Multi-use paths accommodate the off-road movement of both pedestrians and cyclists (Delaney, Parkhurst, & Melia, 2017). Motor vehicle traffic on the multi-use paths is typically restricted to maintenance vehicles only, and local traffic is prohibited (US Federal Highway Administration, 2017). Conventional streets are also present in the study area. These streets do not feature any markings or separation for cyclists from motor vehicles, but bikes are permitted to use them. These streets are local and collector-type streets in the area, which have a lower traffic volume than arterial roads, allowing them to be used as viable cycling route options in areas with poor or no cycling infrastructure. Figure 3a to Figure 3d shows the types of cycling infrastructure discussed.

[a] Sharrow

[b] Separated Bike Lane



[c] Multi-Use Path *[d] Unmarked Road*

Figure 3: Cycling Infrastructure in Study Area

Sourced by (Google Maps, 2024)

Four different routes between the two locations are chosen for the study to compare the effects that a route would have on preferences with differences in travel time, cycling infrastructure, and pavement condition. Each route is required to have a maximum average travel time of less than 8 minutes to minimize survey fatigue. The routes within the study area tend to have a level topography with an average slope of 2%. For reference, slopes greater than 8% become a challenge for even experienced cyclists (Arkesteijin et al., 2013). Elevation profiles are created using Google Earth Pro to assess the topography of the routes, as seen in Figure A1-A4 in Appendix A.

Each of the four routes is presented in the next section to represent a variety of conditions. Figure 4 to Figure 7 show the routes on the map segmented by cycling infrastructure type with checkpoints separating the change in infrastructure. Route 1 is the Low Junctions route and is created to have the least number of turns while utilizing roads with minimal stop and traffic-controlled intersections. Route 2 is the Low Traffic route and is created to use roads and paths with a low number of motor vehicles, cyclists and pedestrians. This route uses a dead-end street as well as multi-use paths with some paths having little to no pedestrian traffic. Route 3 is the Shortest Distance route and is created to be the most direct route between the origin and destination. Route 4 is the Longest Distance route and was created to utilize sharrows as part of the route at the expense of a longer route.

3.1.2 Route 1 - Low Junctions

The Low Junctions route, also known as Route 1 as shown in Figure 4, features an average travel time of 6 minutes and an average slope of 1.9%. It is comprised of a multi-use path between checkpoints 1 & 2 interacting with cyclists and pedestrians. Between checkpoints 2 & 3, the route consists of a road interacting with transit buses and bus stops along with other motor vehicles. The route has two points of interest. Point A is located at the intersection of Campus Walk and Library Lane and tends to have a high pedestrian traffic volume from AM Peak through to the PM Peak period. Point B is located at the roundabout between Ian Macdonald Boulevard and Founders Road. The roundabout design lacks some modern roundabout design features such as marked crosswalks and yield stop lines. This can be a potential hazard for cyclists using the road as motorists are not required to yield for vehicles within the roundabout nor stop for minor road traffic. The route features the least number of junctions, with 5 left turns and 1 right turn when heading towards 190 Albany Road.

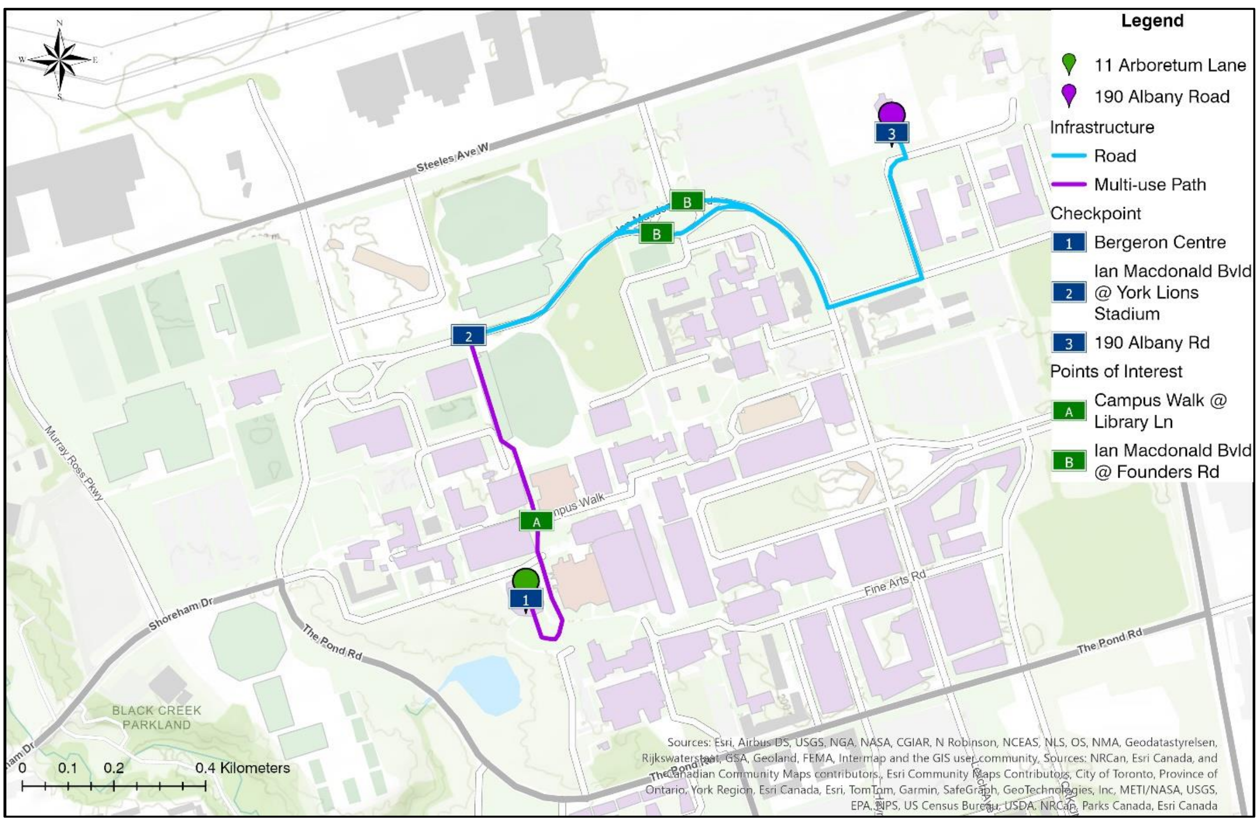


Figure 4: The Low Junctions Route

3.1.3 Route 2 - Low Traffic

The low-traffic route, also known as Route 2 as shown in Figure 5, features an average travel time of 5 minutes and an average slope of 2.1%. It is comprised of a multi-use path between checkpoints 1 & 4 at checkpoints 5 & 6 interacting with cyclists and pedestrians. It also consists of a road between checkpoints 4 & 5 and 6 & 3 interacting with motor vehicles. The route has one point of interest, point A, which is identical to that from route 1. The route requires performing tight turns at checkpoints 5 and 6 due to less space to transition between the multi-use path and the road. The route features the most significant number of junctions, with 6 left turns and 3 right turns heading towards 190 Albany Road.

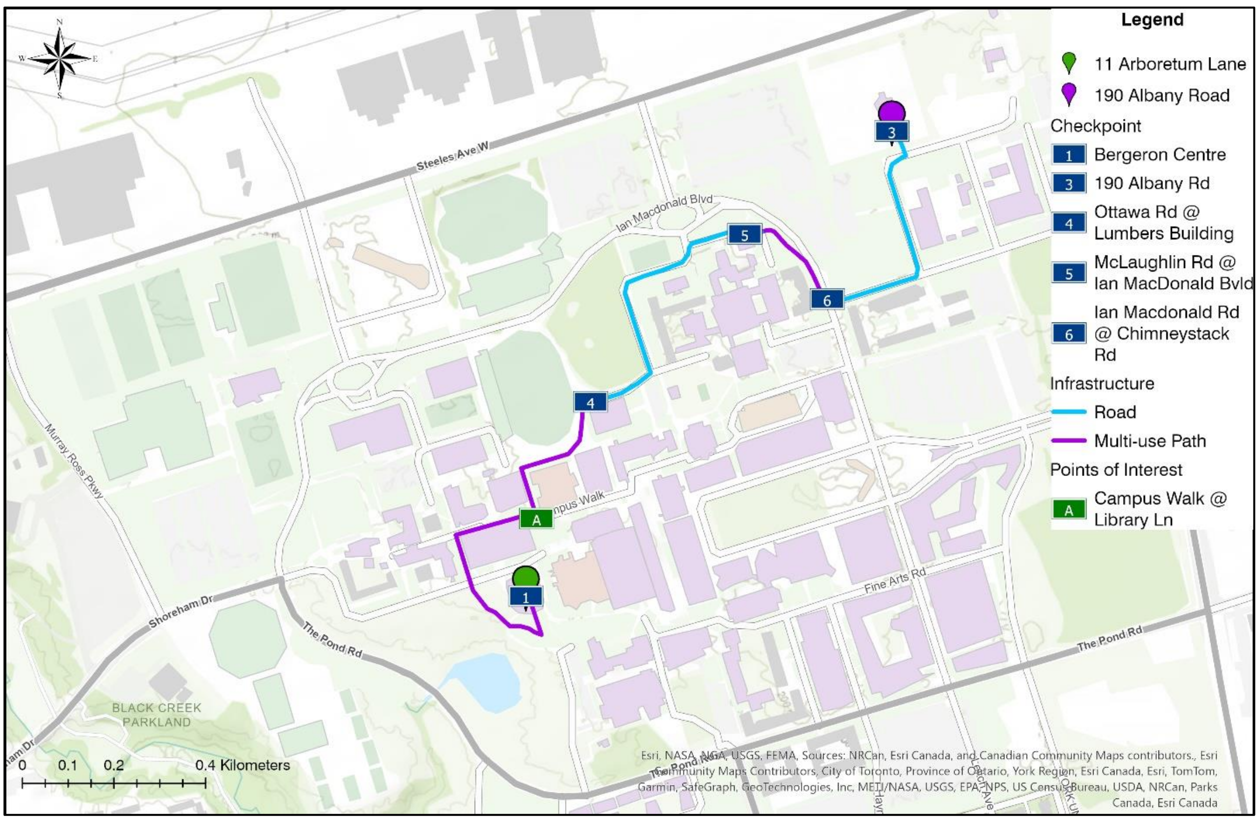


Figure 5: Low Traffic Route

3.1.4 Route 3 - Shortest Distance

The shortest distance route, also known as Route 3 as shown in Figure 6 features an average travel time of 4 minutes and an average slope of 2.2%. It is comprised of a multi-use path between checkpoints 1 & 7 and a road between checkpoints 7 and 3. The route has three points of interest. Point A is identical to the two previous routes. Point D is a high-pedestrian traffic area located at the intersection of Campus Walk and the Lassonde Building. Point E is located on a one-way crescent as part of Vanier Lane at Campus Walk. There is no yield line, sign or stop sign for oncoming traffic to and from the path, nor is there a pedestrian crossing marking. Also, there is a nearby truck loading zone, which requires cyclists to be cautious of any departing and arriving trucks as it is a single-lane road. The route has 5 left turns and 3 right turns towards 190 Albany Road.

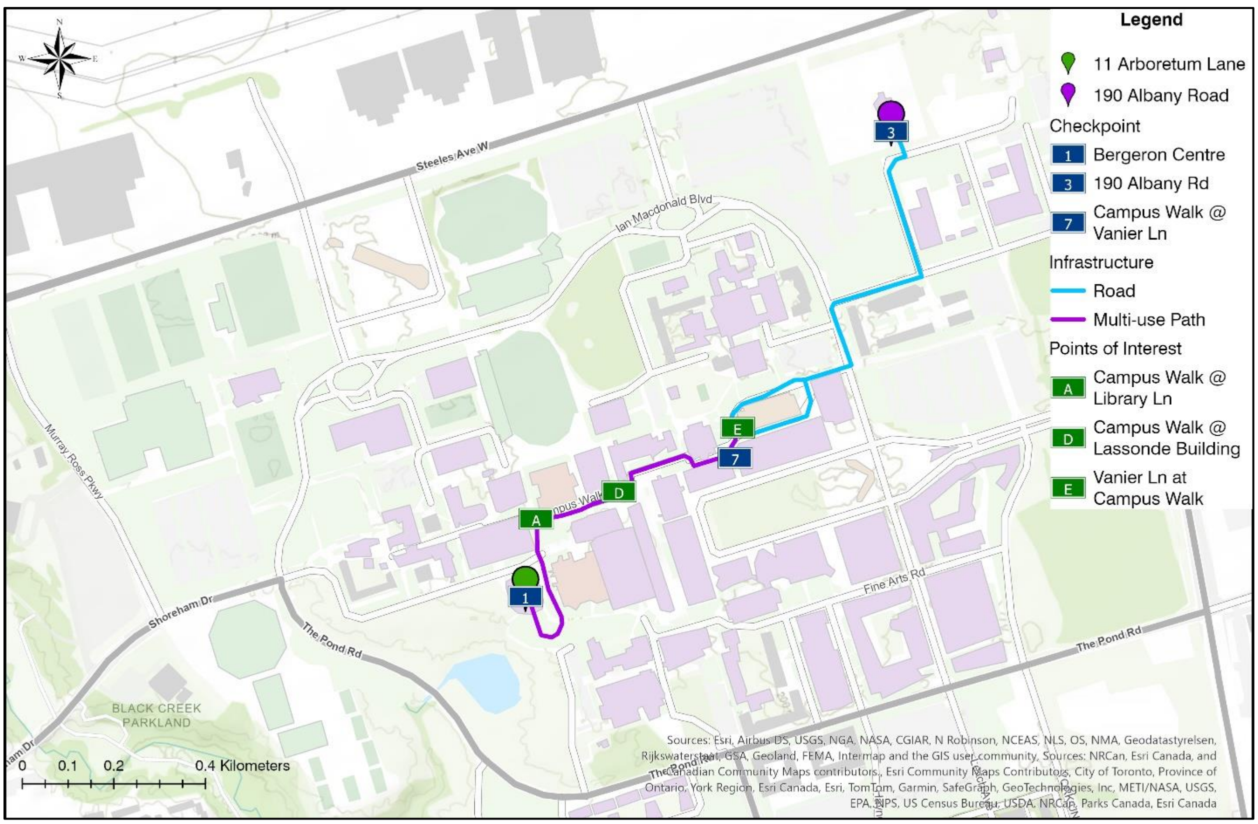


Figure 6: Shortest Distance Route

3.1.5 Route 4 - Longest Distance

The longest distance route, also known as Route 4, as shown in Figure 7, features an average travel time of 8 minutes and an average slope of 1.7%. It is comprised of a multi-use path between checkpoints 1 & 8 and 10 & 11, a road between 9 & 10 and 11 & 3, and a sharrow between checkpoints 8 & 9. The route has 1 point of interest indicated as Point C. These are a pair of unmarked, unpainted speed bumps on Severn Road. This road does not have a sidewalk or path to allow cyclists to avoid the bumps. This would require the cyclists to severely slow down or stop to navigate the speed bumps safely. The road-dominated route features a mix of drop-off/pick-up vehicles along the minor arterial highway as well as curbside transit stops. The route has the most controlled intersections at seven but with the same number of left and right turns as Route 3 with 5 left turns and 3 right turns approaching Albany Road.

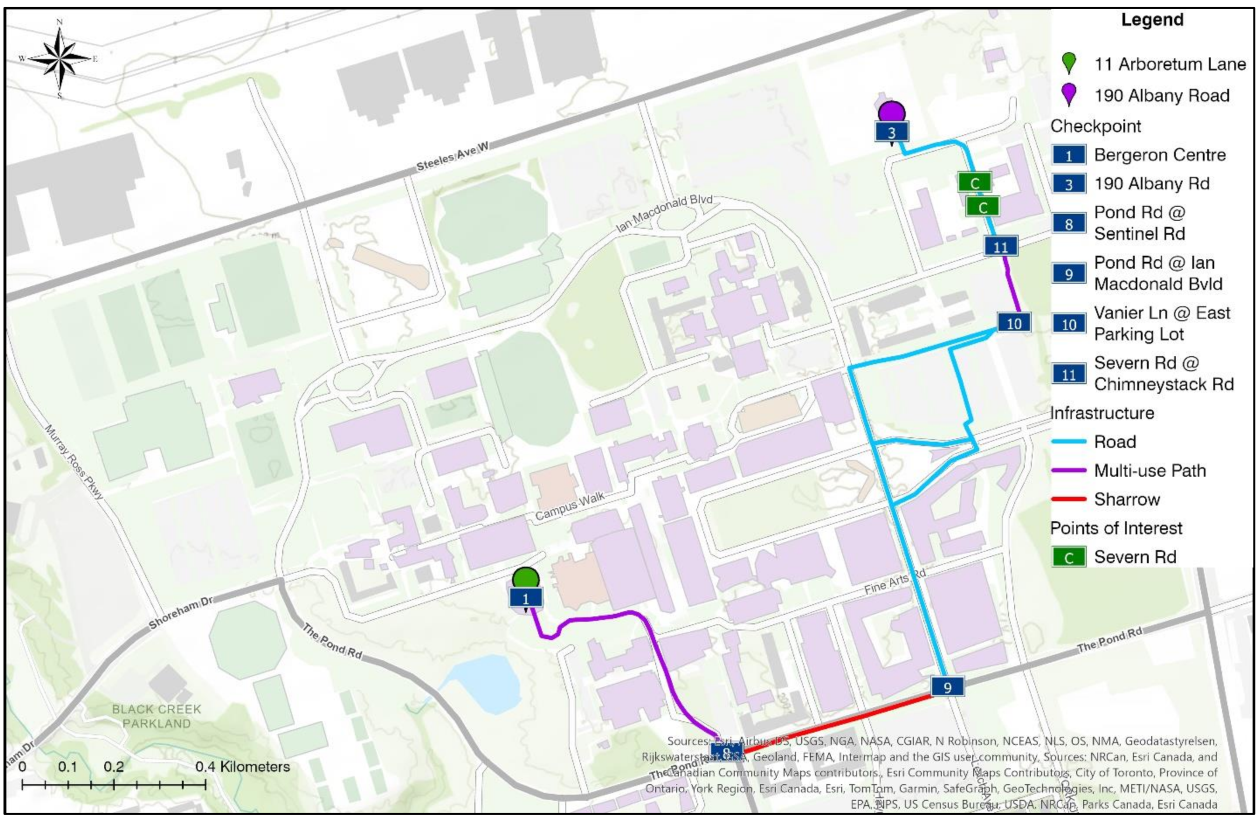


Figure 7: Longest Distance Route

3.1.6 Summary of Route Attributes

Table 2 summarizes the infrastructure type and the distance between checkpoints. Table 3 summarizes the points of interest for each route. A detailed description of the routes chosen can be seen in Table A1 in Appendix A. Checkpoints are locations on the route where the cycling infrastructure type changes such as from multi-use path to road. Points of Interest are locations along the route that negatively affect cycling route choices, such as high traffic volume or sharp turns. Some routes may share the same checkpoints or points of interest in which the same number or letter is used, respectively.

Table 2: Route Checkpoints

Route Name	Start ID	End ID	Infrastructure Type	Distance (km)
Low Junctions	1	2	Multi-Use Path	0.57
	2	3	Road	1.09
Low Traffic	1	4	Multi-Use Path	0.58
	4	5	Road	0.50
	5	6	Multi-Use Path	0.16
	6	3	Road	0.40
Shortest Distance	1	7	Multi-Use Path	0.61
	7	3	Road	0.74
Longest Distance	1	8	Multi-Use Path	0.45
	8	9	Sharrow	0.38
	9	10	Road	0.75
	10	11	Multi-Use Path	0.11
	11	3	Road	0.31

Table 3: Route Points of Interest

Point ID	Route ID	Location	Description
A	1, 2, 3	Campus Walk @ Library Ln	High Pedestrian Traffic
B	1	Ian Macdonald Blvd. @ Founders Rd	Roundabout with no Yielding
C	4	Severn Road	Unmarked Speed Bumps
D	3	Campus Walk @ Lassonde Building	High Pedestrian Traffic
E	3	Vanier Ln @ Campus Walk	One-way crescent road

Table 4 summarizes the characteristics of each route. The average travel time is estimated from Google Maps, assuming a constant speed of 16 km/h and not accounting for waiting for traffic signals or traffic congestion along the route (Wu & Hochmair, 2009). The travel time from Google Maps is referred to as the measured travel time in the thesis. The road category follows the City of Toronto’s Road classification system (City of Toronto, 2018).

Table 4: Route Characteristics

Characteristics	Route 1	Route 2	Route 3	Route 4
Measured Travel Time (minutes)	6	5	4	8
Measured Travel Distance (km)	1.8	1.5	1.4	2.1
Average Slope (%)	1.9	2.1	2.2	1.7
Road Classification(s)	Local	Local	Local	Minor Arterial, Local
Cycling Infrastructure	Multi-use path, Street	Multi-use path, Street	Multi-use path, Street	Multi-use path, Sharrow, Street
Number of Stop and Traffic Light-Controlled Intersections	3(3)*	4(4)	6(5)	8(9)
Number of Left Turns	5(1)	6(3)	5(3)	5(4)
Number of Right Turns	1(5)	3(6)	4(6)	3(5)

**The first number represents travel to 190 Albany Rd., and the second number in parenthesis represents travel to 11 Arboretum Road*

The chosen routes represent some of the most cycled paths in the area according to Strava's global heatmap, as seen in Figure 8. Strava's heatmap data is updated monthly and contains data from over 700 million opt-in users' activities since recording in 2015 (Robb, 2017). The heatmap shows that the routes near the destination are rarely travelled by cyclists compared to the routes near the origin.

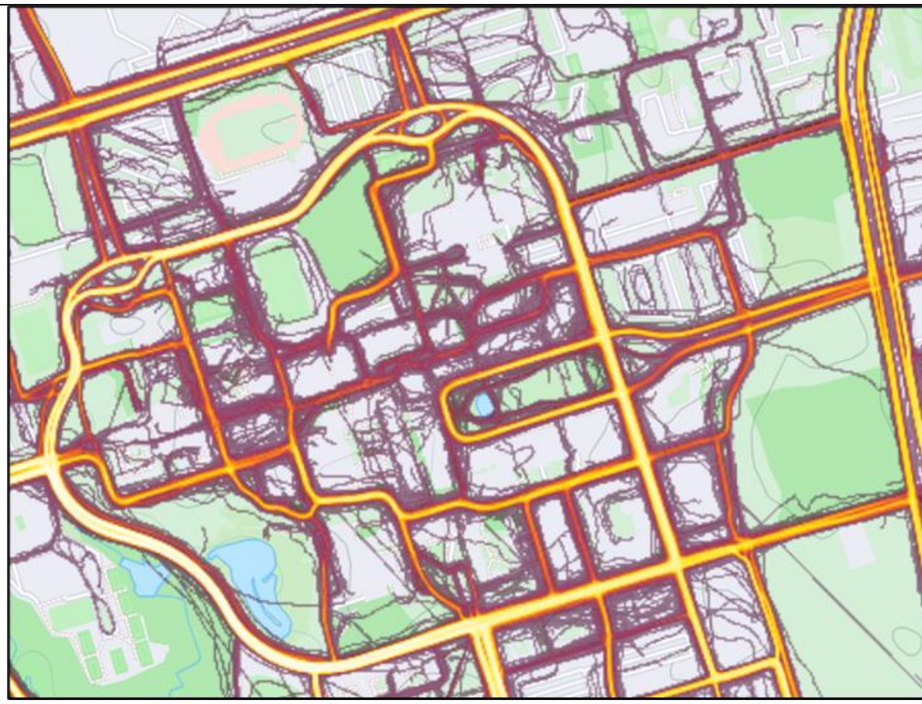


Figure 8: Cycling Activity Heatmap

Adapted from source: (Strava Inc., 2024)

3.2 Data Collection

3.2.1 Variable Definitions

Table 5 summarizes the variables discussed in the literature review and specifies which variables are included in the thesis. The decision-maker category groups variables that are more experience-oriented including comfort and cycling enjoyment. These variables are based on how the participant feels using the ECC. The cyclist characteristics category groups variables related to the cyclist's behaviour such as the cyclist’s demographic, their previous experience cycling or using and ECC and their travel time. The travel time is grouped here because their experience cycling influences how fast or slow the participant cycles on the routes. The infrastructure category groups variables that are typically dependant on the urban infrastructure. The travel distance, pavement condition, slope, dedicated cycling infrastructure and the number of junctions (intersections and turns) are dependant on how the urban infrastructure is designed. Slope is not included due to the routes for the study area primarily using flat terrain. The safety category groups variables that can affect the cyclist’s safety on the routes including collision risk, object frequency and visibility. The final group is related to the battery performance of the ECC. The battery capacity variable is not considered because the routes chosen are of short distances which do not significantly deplete the battery. This would result in participants not being concerned and their behaviour would not be influenced by the battery life as a result.

Table 5: Literature Review Variables

Category	Variables	Literature Examples	Included in Thesis
Decision Maker	Comfort	Holzel (2012) Calvey et al. (2015) Harkey (1998)	Yes
Decision Maker	Cycling Enjoyment	Kreen et al. (2015) Singleton & Clifton (2017) Arellana et al. (2020) Rissel et al. (2016) Singleton (2019) Zander et al. (2013)	Yes
Cyclist Characteristics	Cyclist Demographic	Risel et al. (2016) Howard & Burns (2001) Broach et al. (2010) Ton et al. (2018)	Yes
Cyclist Characteristics	Cyclist Experience	Van Dyck et al. (2012) Calvey et al. (2015) Lachapelle et al. (2021)	Yes
Cyclist Characteristics	Travel Time	Li et al. (2017) Aultman-Hall et al. (1997) Calvey et al. (2015) Krizek (2006)	Yes
Infrastructure	Travel Distance	Jensen et al. (2010) Guo et al. (2017) Calvey et al. (2015)	Yes
Infrastructure	Pavement Condition	Rybarcyk & Wu, (2010) Giubilato & Petrone, (2012)	Yes
Infrastructure	Slope	Calvey et al. (2015) Kreen et al. (2015) Winters et al. (2013)	No
Infrastructure	Dedicated Cycling Infrastructure	Van Dyck et al. (2012) Kreen et al. (2015) Winters et al. (2013) Arellana et al. (2020) Howard & Burns (2001) Hood et al. (2011) Krizek (2006)	Yes
Infrastructure	Object Junctions	Arellana et al. (2020) Vandenbulcke et al. (2014) Jansen & Varotto (2022) Miranda-Moreno et al. (2011) Van Dyck et al. (2012)	Yes
Safety	Collision Risk	Van Dyck et al. (2012) Arellana et al. (2020), Howard & Burns (2001), Lachapelle et al. (2021) Osama et al. (2020)	Yes
Safety	Object Frequency	Chataway et al. (2014), Hull & O'Holleran (2014), Apasnore et al. (2017), Zhao et al., (2013)	Yes
Safety	Cyclist Visibility	Van Dyck et al. (2012) Arellana et al. (2020) Oikawa et. al, (2019)	Yes
Equipment	Battery Capacity	Devshete et al. (2019) Savrum & Poyrazoglu, (2022) Yang et al. (2016)	No

Comfort is defined in this thesis as the actual state of physical and mental ease of cycling in a person (Holzel, 2012). This is also known as behavioural comfort and can affect a cyclist's route preference when the route is physically or mentally discomforting. Cycling enjoyment is defined as the actual state of benefiting or taking pleasure in cycling (Singleton P. A., 2019). Enjoyment can affect comfort because positive feelings experienced when cycling imply that the cyclist is comfortable (Smith, Harrison, & Bryant, 2014). The actual comfort and enjoyment are collected.

Cyclist demographics include the cyclist's gender and age, their cycling experience and their current cycling-related preferences. The demographics allow for categorizing cyclists based on similar patterns and to understand the differences in route selection and in the cycling variables each cyclist category prioritizes. The observed travel time experienced by the cyclist is measured and averaged among all riders of that route. The free flow travel time is not used as this is the travel time experienced without traffic, which is unrealistic for a cargo bike operating during peak traffic periods. The average travel time is chosen for this thesis because it is used widely in cycling route choice studies. Jensen et al. (2010) used the average travel time to compare the average speed of downtown cyclists compared to downtown car users during peak periods to identify the travel time savings experienced when travelling through the area. Their results showed that over a full day, the average speed of cyclists at 13 km/h is significantly different than their maximum speed at 20 km/h, which is under conditions closer to free flow travel speed. The average travel time represents the majority of the trips, whereas the maximum travel time conditions represent just 10% of all trips made. This means that measuring the maximum travel time instead of the average travel time would not represent the majority of cyclists' trips.

The observed travel distance is measured as the total distance travelled on each of the four routes specified for the thesis. The four routes have a fixed distance which would result in the distances being similar among the participants but can be used to identify if the participants deviated significantly from the route due to internal factors such as personal preference and miscommunication or due to external factors such as route closures. The pavement condition data is measured as the number of large bumps and the number of small bumps. The bumps are identified by their vibration value. The values that indicate the bump type are listed in the pavement results section. The number of pavement events is also collected. This is defined as a continuous series of at least 3 or more vibrations. This is chosen because a longer series of intense vibrations results in the event being more noticeable and discomforting to a person (Oroszi, Van Heuvelen, Nyakas, & Van der Zee, 2020). The slope is not measured for the thesis due to the study area being located on flat terrain. The cycling infrastructure is collected spatially, using the percentage of each cycling infrastructure type previously defined. This uses spatial data of the roads and pathways as well as the travel distance data of the participants. Similarly, the number of junctions is measured as the actual number of intersections crossed and the number of turns performed.

The collision risk is measured as the actual number of collisions and the actual number of near misses. The near misses have to occur within 1 metre to be counted according to the minimum spacing for cyclists in Toronto (City of Toronto, 2023). Cyclist Visibility data is collected through the survey, asking participants to recall any problematic areas visually and make observations from the video recording. The object frequency is measured as the actual number of vehicles passing the ECC and pedestrians passing. The vehicle has to be travelling in the same direction or the same lane while the pedestrian has to be travelling across or on the sidewalk closest to the ECC. The battery capacity is not measured for the thesis. The routes within the study area are of short distances less than 2 km each way which would consume a small fraction of the ECCs' maximum range. Since the terrain is flat, the battery capacity is not expected to deplete as rapidly. This results in the effects of range anxiety being negligible.

3.2.2 Data Measurements

Table 6 summarizes the approach used for collecting the variables. The instruments used to collect the data are discussed below in the table. The variables are measured in various forms. One way is through stated experience where the participant states through the survey questionnaire their response. The comfort, cycling enjoyment, cyclist demographic, cycling experience, travel time, travel distance collision risk and cyclist visibility are measured as stated experience. Another way is through the observed or actual data. This is measured through an instrument that records the variable during the study. The comfort, travel time, travel distance and pavement condition are measured through the observed data. The cycling infrastructure is measured as the percentage of the total distance travelled on a cycling infrastructure type.

The variables are collected as certain data types. The continuous data type is used to collect values that have a range of possible measurements. The observed comfort, travel time, travel distance, and cycling infrastructure used are collected as continuous data. The rank data type is used to provide a meaningful order to variables that cannot be precisely measured. The stated comfort and the cycling enjoyment are measured using a rank variable. The dummy variable type is an indicator variable used to represent the data as one or more numerical inputs based on the options provided.

The cyclist demographic and cycling experience are converted to dummy variables from the survey results. The discrete variable type is used when there is a finite number of values that can be recorded. The pavement condition, collision risk, object frequency and visibility are collected as discrete variables.

Table 6: Variable Collection Methods

Variable	Collection	Measurement	Data Type
Comfort	Gyroscope, Video Recording, Survey	Observed, Stated Experience	Continuous, Rank
Cycling Enjoyment	Survey	Stated Experience	Rank
Cyclist Demographic	Survey	Stated Experience	Dummy
Cycling Experience	Survey	Stated Experience	Dummy
Travel Time	Strava, Survey	Observed, Stated Experience	Continuous
Travel Distance	Strava, Survey	Observed, Stated Experience	Continuous
Pavement Condition	Gyroscope, Video Recording, Survey	Observed	Discrete
Dedicated Cycling Infrastructure	Google Earth, Strava	Percentage of total distance by type	Continuous
Object Junctions	Google Earth	Observed Count	Discrete
Collision Risk	Video Recording, Survey	Observed Count, Stated Experience	Discrete
Object Frequency	Video Recording	Observed Count	Discrete
Cyclist Visibility	Survey	Observed Count, Stated Experience	Discrete

<u>Strava data</u>

GPS data, including the observed route of the ECC during the ride, is collected using an internet and GPS-connected smartphone running Strava, a fitness tracking app that records the route travelled as well as the travel time and travel distance of the route (Strava Inc., 2024). The app has accurate route tracking as it is used to collect preliminary information on the potential routes in the area before the study. The GPS coordinate data is outputted as a file containing the latitude and longitude coordinates of the data points recorded that can be used in mapping software to visualize the route taken. The travel time is given as the total time elapsed between the start and end of the recording in minutes with a visual tool to see the location of the participant at that time. This is the same for the travel distance given in km. The speed is shown as the average speed in km/h as well as the maximum speed achieved by the participant. These values are manually recorded in a spreadsheet from the recorded route.

Kinematic Data

Kinematic data, including the acceleration of the ECC, is collected using a Wit Motion gyroscope. The gyroscope communicates to a smartphone via Bluetooth or wired to a laptop computer. The first option is used for gathering the data since it reduces the amount of equipment needed and allows for easy recording and syncing of the data. The gyroscope records the angle in 3-dimensions, as well as the angular velocity, acceleration, and magnetic field (Wit Motion, 2020). These parameters are calibrated for the sensor before data collection. For this model, only the 3-axis acceleration is considered. The 3-axis acceleration is recorded for each point along each route conducted by the participant. The data is used to compute the level of comfort experienced by the cyclist and quantitatively aid in identifying the pavement condition along the route. The data is outputted as a text file that can be imported into a spreadsheet containing the time every half-second in "hours: minutes : seconds: milliseconds" along with the acceleration of each axis in m/s^2. The half-second data is averaged out with the following half-second data point to express the results in seconds. Other data recorded includes the rotation of the gyroscope, the magnetic field of the device and the temperature of the device. These three datasets are not used in any of the results and analyses.

Video Route Data

A Go Pro Hero 11 Video Camera is actively recording video footage of the ECC ride for each route travelled. The footage has timestamps expressed as "hours: minutes: seconds" embedded in the file and is used to qualitatively aid in identifying the pavement condition along the road as well as have recorded footage of any potential near misses that occur during the ride with other moving or stationary objects (ex., vehicle, pedestrian, etc.). This is done in Adobe Premiere Pro, a video editing tool that allows us to see frame by frame the timestamped footage. The footage can be manually matched with the gyroscope and Strava data. The passing cars and pedestrians are manually counted from the footage.

Spatial Data

Spatial data on the road and cycling infrastructure along the routes in the study area is collected for the number of junctions and the presence and amount of dedicated cycling infrastructure along the route. The number of junctions is a simple count of the number along each route in each direction. This includes intersections on multi-use paths connecting to other paths and not building entranceways. This is completed using Google Maps as well as an in-person walk of the routes to confirm the number of turns. The number of left and right turns is determined identically to the number of intersections, with the number of turns representing the minimum needed to navigate the route. More turns may be used by the participants when riding the ECC in the event of obstructions along the route. The percentage of cycling infrastructure used is determined by mapping the route data from Strava, identifying which infrastructure is used, measuring the distance, and dividing it by the total distance of the route.

3.2.3 Data Processing

The input data from the instruments and surveys have to be processed to prepare them for the data analysis. The pre-ride survey requires converting descriptive responses into numbers assigned to each response option, such as 0 for males and 1 for females for the gender response (the participants did not record any other gender). This allows the variables to be used for the route choice model and the AHP tool, as neither tool can interpret text responses. For the 0-10 ratings, they are converted to 0%-100% probabilities for the route choice model. For the AHP weights, the responses are converted into matrices that represent both the importance value chosen by the participant and the variable that the participant found most important. Since the responses have two options, an inverse value is used to indicate that the participant chose the latter value, with the original value indicating the former. This is in line with the AHP process requirements. For the AHP weight section of the survey, participants circle the variable and then write the importance value adjacent to the circled value. For the route ranking section, these are converted to matrices but do not need an importance value written next to the option selected.

Each route recorded on Strava requires manual extraction of the data into a spreadsheet consisting of the experienced travel time, average speed and experienced travel distance for each participant. For the gyroscope, the output file for each route for each participant is imported into a spreadsheet to calculate the comfort value and the number of pavement events. For the video data, a manual count of the number of passing vehicles and pedestrians is conducted. This data is combined with the pre-ride survey and the 0-10 rating survey as inputs for the route choice model.

Chapter Four: Methodology

4.1 Field Survey

The flow chart in Figure 9 is split into five sections: Preparation, Data Collection, Data Recording, Variables and the ECC Score. The variables have been discussed in the previous chapter. Section 4.3 discusses the methodology of the ECC Score. The preparation section includes tasks that are completed before the field survey such as recruitment and establishing how the variables are collected. The data collection section explains how the ECC ride and the survey questionnaire are carried out. The data recording section explains what variables are collected objectively by which instrument aside from the survey. The variables that are collected during the field survey are established in Section 3.2. Some of the survey's properties are established in Section 2.6. The survey is a hybrid RP and SP survey. The survey requires participants to rank ten variables: travel time, travel distance, pavement, cycling infrastructure, junctions, collision risk, object frequency, visibility, sightlines, comfort and enjoyment. Figure 9 below shows the complete methodology process.

The next step is to recruit participants. Figure A5 in Appendix A shows a flow chart of the steps taken to prepare and conduct the ECC ride and survey. As mentioned in Section 2.6, the goal is to have a minimum of 30 participants to have a sufficient sample size. The participants primarily consisted of the York University Keele Campus student body. Ethics approval of the survey and the ECC ride had to be approved by the campus to ensure that all risks in the study are accounted for, and participant data is collected and used ethically. Once approved, flyers, emails, and word-of-mouth advertising are used to recruit participants for the study. Appendix B shows the ethics certificate including the recruitment flyer. A monetary incentive consisting of a $25 gift card of the participant's choice is used to increase recruitment and compensate participants for their time and participation. This is provided to the participants after they complete the ride and survey. Participants are then contacted to arrange the study time and collect preliminary data, including contact information and cycling experience. Participants access an interactive map of the four routes, which shows the various checkpoints and cycling infrastructure types. As a requirement for receiving ethics approval, participants are required to fill out and sign an informed consent form that outlines the benefits and risks of the study. The form is available to the participants to read and is summarized by the facilitator at the start of the study period.

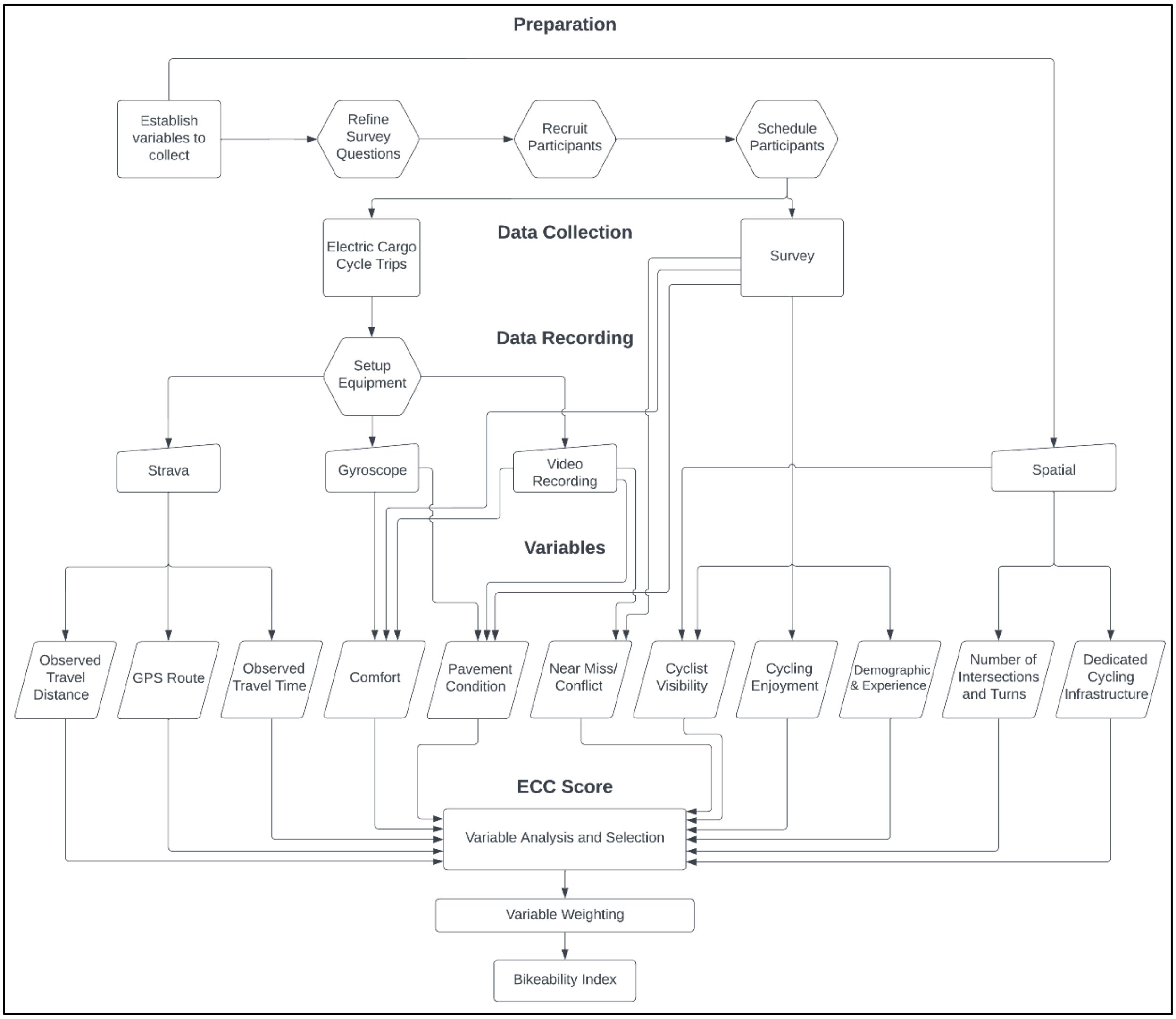


Figure 9: Flow Chart for Developing the ECC Score

The field survey is split into two components: The ECC trips and the Survey itself. The survey questions are answered on paper to avoid digital complications. The survey is designed to be completed within 10 minutes, with 4 minutes spent by the participant to indicate their cycling background and demographic and 6 minutes spent answering questions related to their experience riding the ECC. The survey length is increased to add more questions that simplify the development of the ECC score. This allowed for pairwise ranking between each of the nine variables as well as the pairwise ranking of the four routes based on each variable. This resulted in a survey with 25 questions. The length of the survey is increased by 10 minutes, and many sessions are placed over the 1-hour block by a few minutes. A 15-minute buffer time between consecutive sessions is planned to ensure the facilitator can prepare for the next session before the participant arrives and to account for sessions that are completed beyond the 1 hour. The survey questionnaire is divided into three sections. Appendix C shows the survey questions. The first section known as the Pre-Ride section requires participants to fill out sociodemographic information about themselves, including their gender and age. Also, the participants answered questions related to their cycling experience, conditions that limit them from cycling, such as weather or infrastructure and their familiarity with electric bikes and three-wheeled tricycles. The questions are formatted either as multiple choice, checkboxes or a 0 to 5 scale. These questions are conducted online before the participant's study session or at the beginning of the study.

The second, third and fourth parts of the survey are conducted after the ECC trips due to the need to collect RP data from participant's experience in cycling along the routes. The second section known as the Route & Variable Ratings section requires participants to rank on a scale from 0 to 10 how well each of the nine variables is on each of the routes ridden. The third section is the AHP Weights and Route Rankings. Participants indicate which of the two cycling variables is more important to them for each pairwise combination of variables and how important the variable is to them using the AHP importance scale from 1 to 9. This is answered by indicating next to which variable its importance value. This is done to simplify the input for the weighting process. The route rankings section is similar to the AHP weights except participants did not indicate the importance of choosing a variable from the pairwise comparison. This allows for a global route ranking, which is used to verify the ECC score and AHP weights. The fourth section is a set of short answer questions about the participant's safety experience and opinion on the feasibility of an ECC for last-mile delivery. This allows the participant to identify any collisions or near misses they experienced on the routes and the approximate location. These locations are verified by analyzing the Go Pro Video as discussed in section 5.2.4.

The gyroscope, smartphone and video camera are attached to a Babboe Pro Trike XL, an ECC with a 900 L cargo trunk flanking its two front wheels (Babboe, 2023). The ECC provides up to 25 km/h of electric pedal assist with preset levels of electric assist, which, when combined with pedalling, allows for speeds up to 32 km/h, the maximum speed allowed for ECCs in Ontario (Ministry of Transportation Ontario, 2022). The ECC has gear shifting to use on steep terrain. The gear shift can be adjusted when riding to reduce the difficulty of cycling on certain parts of the route. For the field survey, the electric assist defaults to standard, with the gear shift set to the lowest gear. Figure 10 shows the instrument setup on the ECC. Due to the participants having different physical fitness levels, cycling experience, and experience using ECCs, the ECC is deployed with a 0 kg payload weight, which only included the data collection instruments and did not include observed cargo.

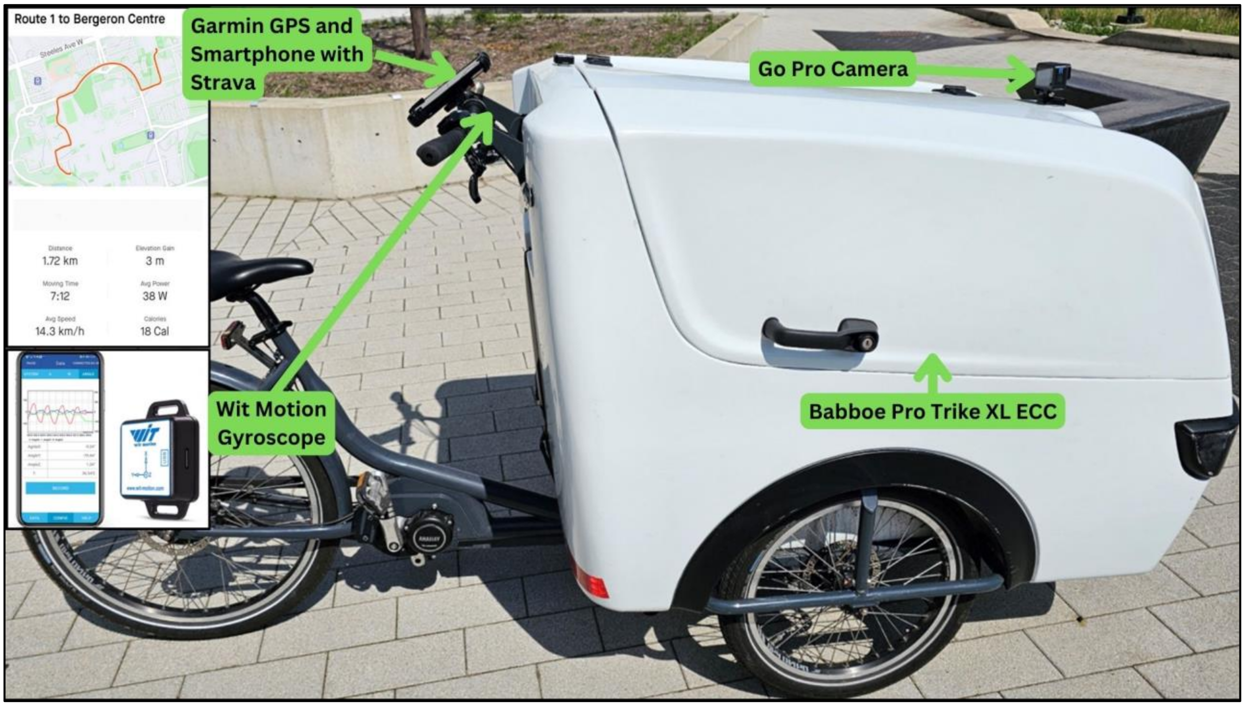


Figure 10: Instrument Setup

The gyroscope is mounted on the frame of the ECC due to the trunk's tendency to vibrate more than the frame, which can exaggerate the observed vibrations the cyclist experiences. The smartphone is mounted on the handlebars to record route travel data via the Strava app and provide route navigation to the cyclist. A Go Pro Hero 10 camera is mounted on the front hood to record video of the ride akin to a dashcam. A Garmin 530 GPS is also attached to the handlebars to record the route travel data and is synced to Strava. This allows for verification of the route travel data. The participant is given up to 10 minutes to practice riding the ECC and become comfortable in using it. Forty minutes is allocated for riding on the routes even though the longest of the four routes takes an average of 8 minutes to complete. The order of the four routes is randomized to identify if the order of the routes affects the variables. The participant rides on two of the routes toward the destination and the other two toward the origin. The instruments manually record each route, requiring the starting and stopping of data collection at the start and end of each route.

Participants are offered a sanitized helmet to use during the study. The survey facilitator rides behind the participant in a nearly identical ECC to ensure they are following the route and aiding during the ride.

4.2 Survey Updates

Throughout the field study, changes are made to the survey to reduce the time spent. First, due to the multiple-choice portion of the survey being lengthier than the verbal questions, the verbal questions are conducted immediately after the ride to ensure that participants can accurately recall their experiences in detail. Second, the time for participants to try out the ECC before cycling is reduced from 10 minutes to 4 minutes with a test route that emphasizes turning with the ECC due to its requirement of wider turning radii compared to a conventional bicycle. This saw participants adjust to the ECC in less time and are more confident in starting the routes. This, together with Part 1 of the survey being filled out online by the majority of participants, resulted in the majority of studies being completed within an hour or less. Third, on route 4, due to poor pavement performance along the route that impacted the ability to cycle at a higher speed, a second branch of the route is provided. The original route is designated as 4B, and the new branch is 4A, where the participant would continue to pass the parking lot on Vanier Lane and turn left at Ian Macdonald Boulevard. The participant is made aware of these branches and would indicate to the facilitator which branch they wanted to cycle on beforehand. This is shown below in Figure 11.

Route 4A is similar to Route 4B, such that the travel distance of the route is almost identical but allows for fewer turns and longer linear route segments, which may allow for higher cycling speeds to be achieved while both using identical cycling infrastructure. Fourth, the facilitator would sometimes request to overtake the participant to assist in route navigation to alert and avoid severe pavement distress as well as parts of the route being unexpectedly blocked by pedestrians or vehicles. This is most common along Route 2 and Route 3.

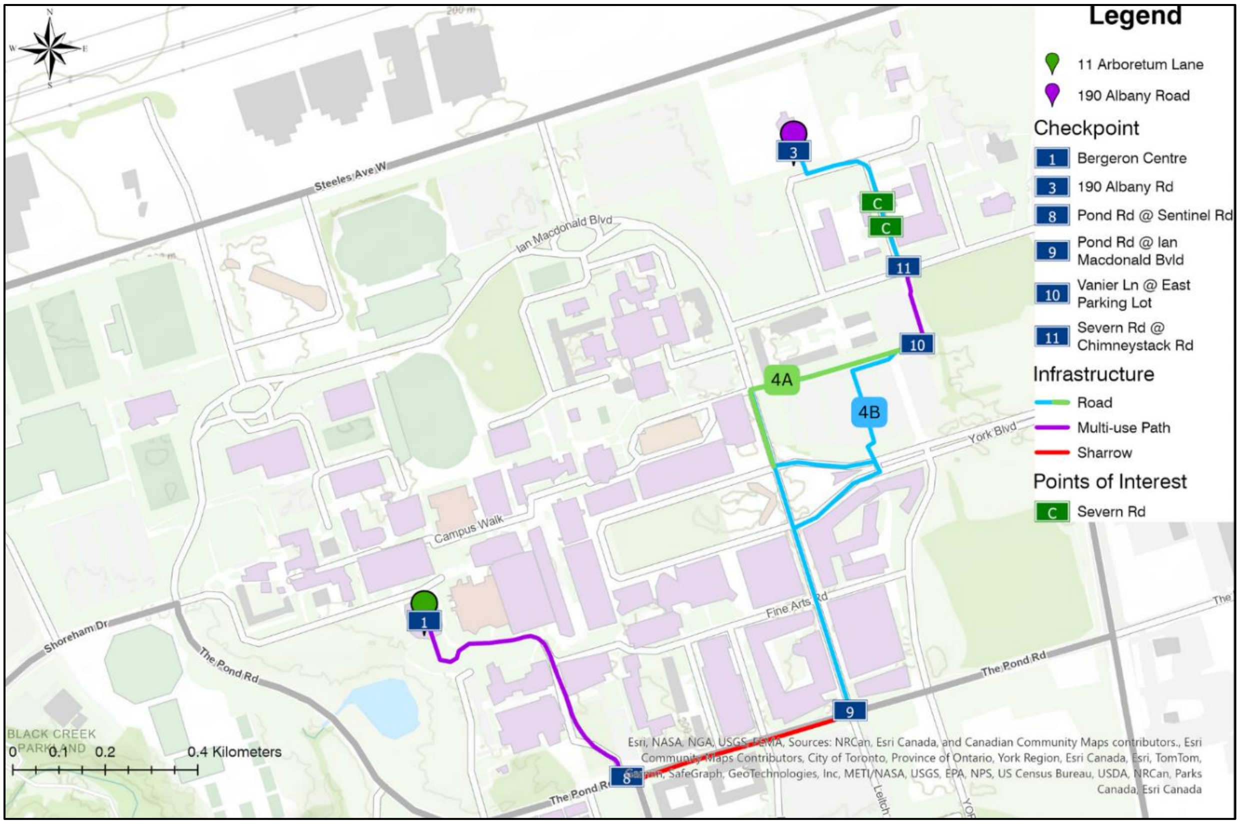


Figure 11: Route 4 Branches

The field survey is conducted for 4 weeks, from May 22nd, 2024, to June 14th, 2024, from Monday to Friday between 9:00 AM and 5:00 PM. The weather conditions are primarily sunny and dry, with temperatures between 20 C° and 27 C° depending on the time of day. On 3 of the days, participants encountered severe weather, which prompted a cancellation or partial completion of the ride. A total of 43 participants participated in the study. 30 of the 43 participants completed all four routes the rides and the survey. However, variables such as cycling at a low speed, disinterest in completing the study or external variables such as severe weather or arriving late resulted in two of the four routes being ridden on. Despite this, affected participants can answer applicable parts of the survey. The Route & Variable Ratings section of the survey is not affected, and neither is the first set of questions of the AHP weights section. Half of the Route & Variable Ratings section and a quarter of the AHP weights section relating to route rankings are unable to be answered due to the questions requiring all four routes to be ridden on. The partial completions did not affect the participant's ability to receive the monetary incentive as the consent form indicates that they do not have to complete the routes to earn it.

Due to the participants cycling on 2 of the 4 routes, 10 of the sessions are missing the remaining 2 routes. An additional 11 had missing data components due to instrument issues such as the batteries in the camera depleting mid-ride or connection issues between the phone and the gyroscope from the devices overheating in hot weather. The absence of this data affected the number of observations as 4 responses to the Pre-Ride survey were incomplete, 6 of the gyroscope readings were partially recorded 1 did not record at all and, 4 video recordings did not record or save. For the partial gyroscope recordings, since the majority of the data is recorded properly, these results are kept. For observations where data from multiple instruments are missing, these are removed which resulted in 4 observations removed out of a total of 43. The remaining 39 observations can be kept as inputs for the ECC score.

4.3 Analytical Hierarchy Process

AHP is used to generate weights for variables in the ECC Score. Previous bikeability indices used regression models to determine their weightings instead of AHP. Using AHP instead of a regression model to develop the weights has some advantages. Regression models are beneficial when outcomes need to be predicted from quantitative variables. For qualitative variables, their inclusion as dummy variables in a regression model can cause multicollinearity in the model which affects the stability and interpretation of the coefficients (Kammen, 2014). This is seen in the previous bikeability indices where almost all of the variables were quantitative with some variables such as comfort converted to a dummy variable to quantify them at the cost of information loss (Kammen, 2014). AHP can handle both types of data effectively by incorporating qualitative results as pairwise comparisons which can be challenging to quantify for other models. The purpose of using the AHP for the score is to assist in determining which variables are prioritized the most by ECC users.

The weights are determined by applying the geometric mean method to each participant's responses to the pairwise comparisons from the AHP weights section of the survey. The responses require choosing one of two variables that is most important and rating its relative importance from 1 to 9. Each participant response is converted into a matrix with each variable from the AHP survey questions as shown in Figure 12a. The values are populated in the lower triangle of the matrix. A value with a negative sign indicates the participant prefers the variable in the left column whereas a positive sign indicates the participant prefers the variables in the top row. The diagonal of each matrix is expressed as 1s with the lower triangle representing the original responses as seen in Figure 12b. The upper triangle of the matrix is transposed from the lower triangle with values inversed to reflect the participant's opposite selection in the upper triangle as shown in Figure 12c. Then, if the participant had a positive value in the cell, the number is kept whole, but if they had a negative value, the number is replaced with its inverse expressed as a decimal. This is shown in Figure 12d.

12A	**Travel Time**	**Travel Distance**	**Cycling Infrastructure**	**Pavement Condition**	**Junctions**	**Risk of Collision**	**Object Frequency**	**Visibility**	**Sightlines**	**Comfort**	**Enjoyment**
Travel Time	-										
Travel Distance	6	-									
Cycling Infrastructure	2	-1	-								
Pavement Condition	1	-1	-3	-							
Junctions	-1	-1	1	-2	-						
Risk of Collision	-4	-3	-3	-4	-3	-					
Object Frequency	3	2	2	2	3	4	-				
Visibility	-2	-2	-4	-3	-3	3	-2	-			
Sightlines	-3	-2	-2	-3	-3	4	-3	2	-		
Comfort	1	3	1	-2	3	3	-2	3	-2	-	
Enjoyment	2	-2	-2	1	3	3	-2	3	3	-3	-

[a]: Matrix with Pairwise Comparisons

Travel Time	1										
Travel Distance	6	1									
Cycling Infrastructure	2	-1	1								
Pavement Condition	1	-1	-3	1							
Junctions	-1	-1	1	-2	1						
Risk of Collision	-4	-3	-3	-4	-3	1					
Object Frequency	3	2	2	2	3	4	1				
Visibility	-2	-2	-4	-3	-3	3	-2	1			
Sightlines	-3	-2	-2	-3	-3	4	-3	2	1		
Comfort	1	3	1	-2	3	3	-2	3	-2	1	
Enjoyment	2	-2	-2	1	3	3	-2	3	3	-3	1

[b]: Diagonal Replaced with 1s

1	6	2	1	-1	-4	3	-2	-3	1	2
6	1	-1	-1	-1	-3	2	-2	-2	3	-2
2	-1	1	3	1	-3	2	-4	-2	1	-2
1	-1	3	1	-2	-4	2	-3	-3	-2	1
-1	-1	1	-2	1	-3	3	-3	-3	3	3
-4	-3	-3	-4	-3	1	4	3	4	3	3
3	2	2	2	3	4	1	-2	-3	-2	-2
-2	-2	-4	-3	-3	3	-2	1	2	3	3
-3	-2	-2	-3	-3	4	-3	2	1	-2	3
1	3	1	-2	3	3	-2	3	-2	1	-3
2	-2	-2	1	3	3	-2	3	3	-3	1

[c]: Negative Values Assigned

1.00	6.00	2.00	1.00	1.00	0.25	3.00	0.50	0.33	1.00	2.00
6.00	1.00	1.00	1.00	1.00	0.33	2.00	0.50	0.50	3.00	0.50
2.00	1.00	1.00	3.00	1.00	0.33	2.00	0.25	0.50	1.00	0.50
1.00	1.00	3.00	1.00	0.50	0.25	2.00	0.33	0.33	0.50	1.00
1.00	1.00	1.00	0.50	1.00	0.33	3.00	0.33	0.33	3.00	3.00
0.25	0.33	0.33	0.25	0.33	1.00	4.00	3.00	4.00	3.00	3.00
3.00	2.00	2.00	2.00	3.00	4.00	1.00	0.50	0.33	0.50	0.50
0.50	0.50	0.25	0.33	0.33	3.00	0.50	1.00	2.00	3.00	3.00
0.33	0.50	0.50	0.33	0.33	4.00	0.33	2.00	1.00	0.50	3.00
1.00	3.00	1.00	0.50	3.00	3.00	0.50	3.00	0.50	1.00	0.33
2.00	0.50	0.50	1.00	3.00	3.00	0.50	3.00	3.00	0.33	1.00

[d]: Negative Values Inversed

Figure 12: Pairwise Response Conversion Example

The weights are calculated using an AHP calculation software of choice, Spice Logic (Spicelogic, 2022). The results are manually replicated by hand to confirm that the process of computing the weights using the average normalized geometric mean is followed by Spice Logic. Through the use of an Excel spreadsheet, we can replicate its sample calculations with identical results.

The individual participant weights are then aggregated together to compute the overall AHP weights. Each participant's AHP weights are aggregated together using the aggregation of individual judgments method with the geometric mean. The geometric mean is calculated using the weighted sum as seen in equation (1).

$$\text{Geometric Mean} = \sum (x * w) \tag{1}$$

Where x is the variable and w is the AHP weight associated with x.

The level of inconsistency in each participant's response matrix is then checked to identify if the responses are consistent among the different pairs of variables. The AHP consistency ratio method is used to compute this. The consistency index CI is then computed using Spice Logic, as seen in equation (2), to calculate the inconsistency ratio as seen in equation (3).

$$\mathrm{CI} = \frac{(\lambda - n)}{(n - 1)} \tag{2}$$

Where n is the dimension of the matrix and λ is the principal eigenvalue.

$$\text{Inconsistency Ratio} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{3}$$

Where CI is the consistency index and RI is the random index based on randomized participant results.

The number of variables that remain depends on the final weights of the model and the inconsistency ratio. The ECC score for each variable is calculated as a standardized weight depending on the relationship between a variable and a high score. For example, a route with a higher travel time results in a lower score whereas a route with a higher pavement rating results in a higher score. The former uses cost criterion scoring as seen in equation 4 while the latter uses benefit criterion scoring as seen in equation 5. Table 7 lists the formula used to compute the score for each variable. The variables are standardized such that the score ranges from 0 to 10 and the standardized values are applied to each route. This requires setting boundary conditions for the inputs to avoid very large numbers from skewing to a high score and vice versa when using very small numbers. These boundaries can be tailored to each variable as the greatest value of the variable among the routes and as the lowest value. The score for each route is calculated as the sum of the individual scores then expressed out of 10 as seen in equation 6. This allows the score to be compared to the 0-10 survey results including the overall route attractiveness rating response.

$$x_i' = \frac{x_i^{max} - x_i}{x_i^{max} - x_i^{min}} \tag{4}$$

Where x_i' is the score for each variable i, x_i^{max} is the greatest value of the variable for the route, x_i is the weight and, x_i^{min} is the lowest value of the variable for the route.

$$x_i' = \frac{x_i - x_i^{min}}{x_i^{max} - x_i^{min}} \tag{5}$$

Where x_i' is the score for each variable i, x_i^{max} is the greatest value of the variable for the route, x_i is the weight and, x_i^{min} is the lowest value of the variable for the route.

Table 7: Criterion Formula for Variables

Variable Name	Criterion Type
Travel Time	Cost
Travel Distance	Cost
Cycling Infrastructure Percentage	Benefit
Pavement Condition Rating	Benefit
Junctions	Cost
Safety Rating	Benefit
Object Frequency	Cost
Visibility Rating	Benefit
Sightlines Rating	Benefit
Comfort Rating	Benefit
Enjoyment Rating	Benefit

$$ECC\ Score_u = \sum_{n}^{1} x_i' * 10 \tag{6}$$

Where u is the route number and n is the number of variables inputs.

4.4 Route Choice Model

The route choice model is represented by an ordered logit model. An ordered logit model is commonly used in transportation planning for ordinal outcomes including mode choice and travel behaviour studies *(Levinson, 2024)*. An ordered logit model is developed to have more explanatory power to explain variations of the dependant variable based on several independent variables. This is explained using the statistical significance of the outputs of the model. A higher statistical significance indicates that those variables contribute the most to the model. The AHP is unable to provide an explanatory connection between the variables themselves and the final weights. The ordered logit addresses this by providing a connection between the variables and a dependant variable. The average overall route attractiveness rating is the dependant variable in this thesis. Together with the AHP, this allows us to identify if a variable should remain in the score despite having a high AHP weight or should be removed if it has a low correlation and is not heavily weighted.

The ordered logit model uses a single utility function for all possible alternatives *(Train K. , 2009)*. In this thesis, the alternatives are based on survey results from participants rating each route from

0 to 10 with 0 indicating a very poor route and 10 indicating an excellent route. The ordered logit model is estimated using NLogit software.

The observed utility Vi for each route is computed from the individual variables as below:

$$V_i = \beta_0 + \beta_1 * X_{1i} + \beta_2 * X_{2i} + \cdots + \beta_n * X_{ni} \tag{7}$$

Where: β_0 is a constant term, n is the total number of variables and the following parameters β determine the influence that X has on the observed utility. The utility is related to probabilities for each alternative based on threshold values that are estimated along with the parameters. However, an exception is the zero threshold which is fixed to a value of 0 when using NLogit software. In this thesis, the probability of a route receiving a rating of 0 can be calculated as follows:

$$\mathrm{Prob}(0) = \frac{\exp^{0-V_i}}{1+\exp^{0-V_i}} \tag{8}$$

The probabilities of successive alternatives from 1 to 9 utilize threshold values can be calculated as follows:

$$\mathrm{Prob}(n) = \frac{\exp^{u_n-V_i}}{1+\exp^{u_n-V_i}} - \frac{\exp^{u_{n-1}-V_i}}{1+\exp^{u_{n-1}-V_i}}\ , 1 \leq n \leq 9 \tag{9}$$

Where: n represents the alternative value, while u_n and u_{n-1} represent threshold values. The final alternative rating of 10 can be calculated using the last threshold value as follows:

$$\mathrm{Prob}(10) = 1 - \frac{\exp^{u_9-V_i}}{1+\exp^{u_9-V_i}} \tag{10}$$

An expected rating value for each route can be generated using these equations. The route with the highest expected rating represents the best route for ECCs based on the input data. The model is based on the independent variables from the Route & Variable Ratings section of the survey including the "Overall Route Attractiveness Rating.".

The model is estimated using NLogit6, a tool that is used to compute various logit models, including ordered logit. Due to challenges with the data collection instruments, 110 of the 148 results are missing data from the survey results and are replaced in the dataset by taking the average value. In addition, the data is treated as a panel since each participant provided an answer for each completed route. This is an unbalanced panel since some participants completed all four routes, while other participants only completed two or three routes. A person ID is generated to group participants for the panel. A fixed effects panel is utilized for this thesis to control for unobserved variables of each participant. The results in the fixed effects panel model focus on the impact of differences between routes.

The ordered logit model is used in this thesis to identify the variables that are the most statistically significant. This helps determine the variables to keep in the ECC score developed from AHP weight results.

Chapter Five: Field Study Results

The following sub-sections discuss the results from the field study used as inputs for the ECC score weights. The survey results are discussed in section 5.1 while the device outputs are discussed in section 5.2. Section 5.2.2 introduces a method to group participants depending on their speed and cycling experience.

5.1 Survey Results

The survey questionnaire is divided into three sections. Appendix C shows the survey questions. The first section is the Pre-Ride section. This section requires participants to fill in sociodemographic information about themselves and answer questions related to their cycling experience before the ride. The second and third sections of the survey are conducted after the ECC trips. The second section is the Route & Variables Ratings where participants ranked on a scale from 0 to 10 how well each variable preformed for each route. The third section of the survey is the AHP weights and route ranking questions. The AHP weights questions require participants to answer for each pairwise combination of variables, which of the two variables is more important to them and how important the variable is to them using the AHP importance scale from 1 to 9. The route ranking questions are similar except the importance value is not indicated.

5.1.1 Pre-Ride Survey

This section discusses the results obtained from the Pre-Ride Survey. The results are presented in the same order that the questions are given to the participants as seen in Appendix C. In Chapter 5.2.2 the results from these questions are used to group participants into two functional categories A total of 39 people participated in the field study, well above the minimum goal of 30 participants. Figure 13 and Figure 14 show the demographic results from Part 1 of the survey. The participants consisted of 27 undergraduate students, 8 graduate students and 4 older students and adults. The participants are subsequently categorized into three age groups: Ages 18-22 represent the typical undergraduate student age, ages 22-25 represent the typical graduate student age, and 26+ years represent older adults. Out of those surveyed, 29 identified as male while the remaining 10 identified as female.

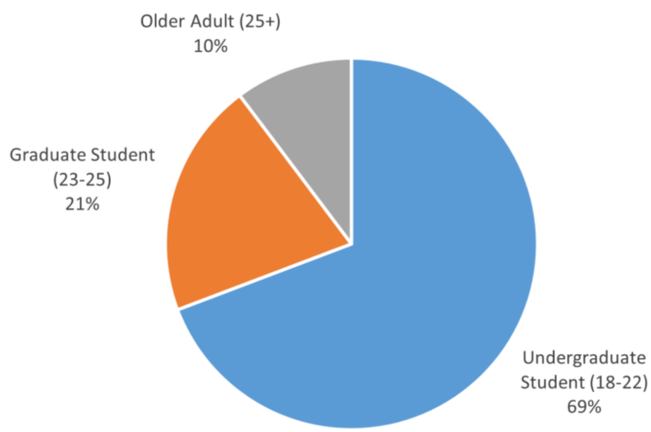


Figure 13: Participant Age Results

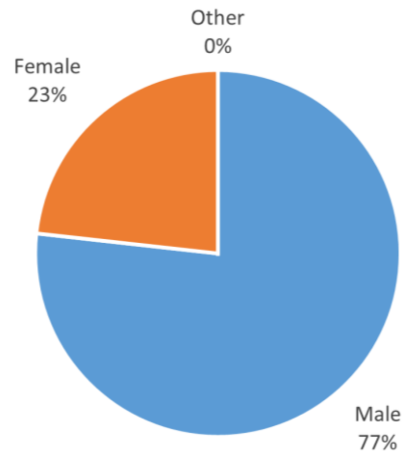


Figure 14: Participant Gender Results

Figure 15 shows that 23 of the participants typically ride a road bicycle without electric assistance, and 17 of the participants usually ride a trail bicycle instead. Only 2 people have ridden an ECC, and 4 participants have used a conventional bicycle with electric assist. Figure 16 shows that 15 of the participants cycled for less than 1 day a week, 18 participants cycled for 2 to 3 days, and 6 participants cycled for 4 days a week or more. Most participants cycled as a form of exercise or leisure, with fewer participants indicating that they cycle for day-to-day purposes such as commuting or goods transport. It is found that 11 participants recorded that they do not regularly ride a bike, 5 recorded that they rarely ride a bike at all currently with 2 of these participants also indicating that they do not cycle due to lack of interest. The lack of experience is observed during the ECC ride as the 2 participants are going significantly slower than expected and explicitly stated to the facilitator that they did not want to continue participating after cycling on 1 or 2 of the four routes. Still, the majority of participants were committed to completing the study and cycled to the best of their ability with only 10 of the 39 participants cycling on 2 routes.

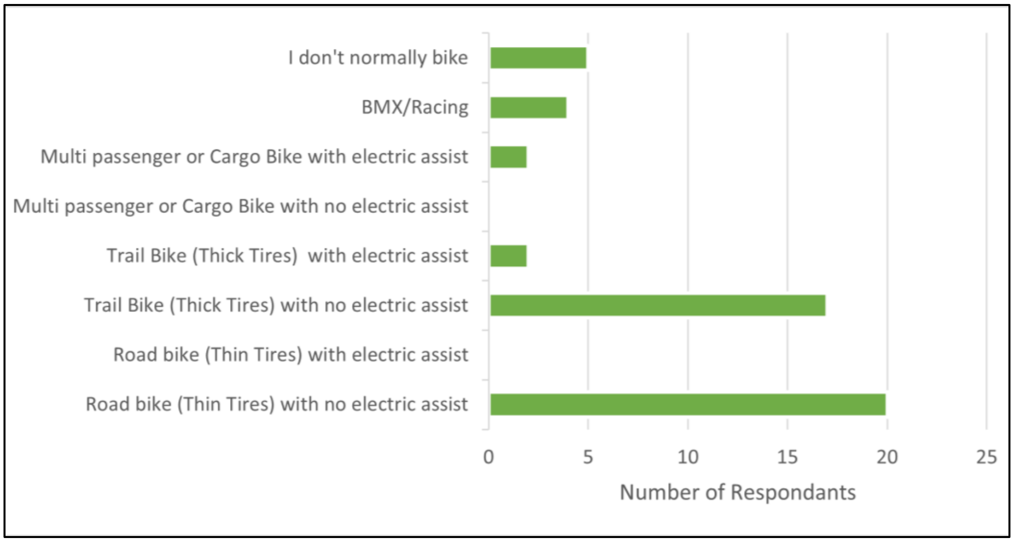


Figure 15: Cycling Equipment Responses

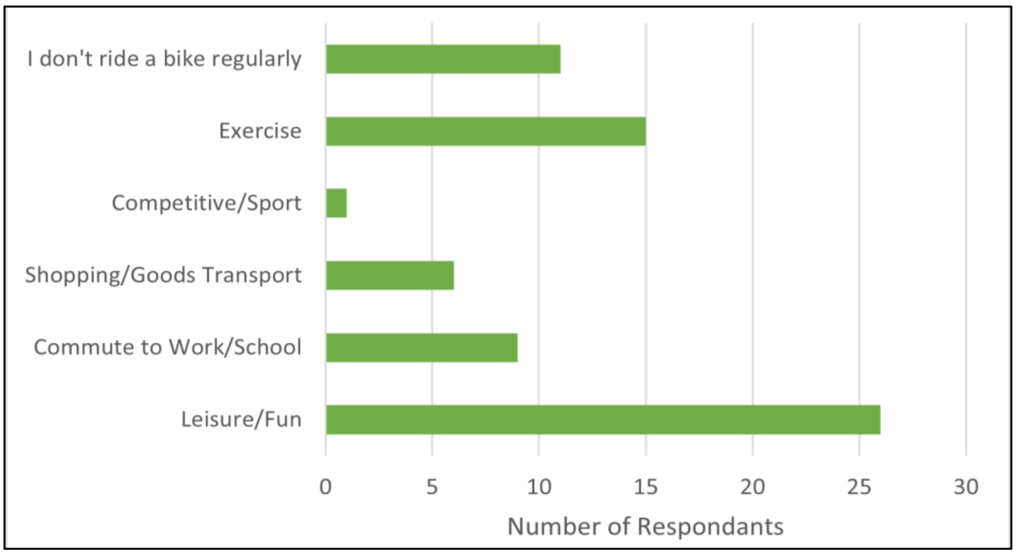


Figure 16: Ride Purpose Responses

Figure A6-A9 in Appendix A visualizes the results related to the participants' physical fitness and the weather conditions in which they cycle. The participant's physical fitness is categorized as 0-1 for those that are less fit, 2-3 for those somewhat fit and 4-5 for those that are very fit. Almost all except for 2 of the participants rated themselves as somewhat fit or very fit, with an even split between the two. Weather conditions are categorized as Dry, Rain and Snow, with the temperature conditions categorized as Very Cold (less than 0 ⁰C), Cold (0 ⁰C - 10 ⁰C), Cool or Temperate (10 ⁰C - 25 ⁰C) and Hot (greater than 25 ⁰C). Very few participants cycled in the rain and the snow, with results of 10 and 1, respectively. This pattern is similar for the temperature, where 2 and 6 participants rated that they cycle in cold temperatures, respectively.

A question is given to understand the main deterrents to cycling among participants as seen in Figure 17. Winter weather is the main deterrent that stops the participants from cycling more, with 30 participants selecting it. The lack of cycling infrastructure, as well as destinations being too far, are also significant deterrents from cycling more, with 18 and 22 selections from participants. Figure 18 shows the top types of cycling infrastructure avoided by participants. This includes 12 participants avoiding the sidewalk, 23 participants avoiding the road itself, 2 avoiding barrier-separated bike lanes, 6 avoiding painted bike lanes and sharrows and 7 avoiding multi-use paths.

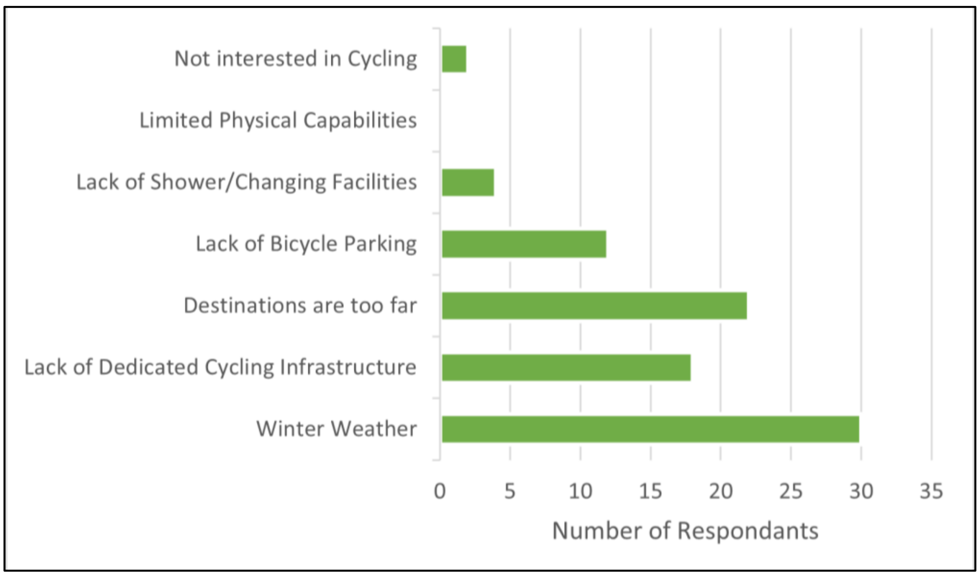


Figure 17: Cycling Deterrent Responses

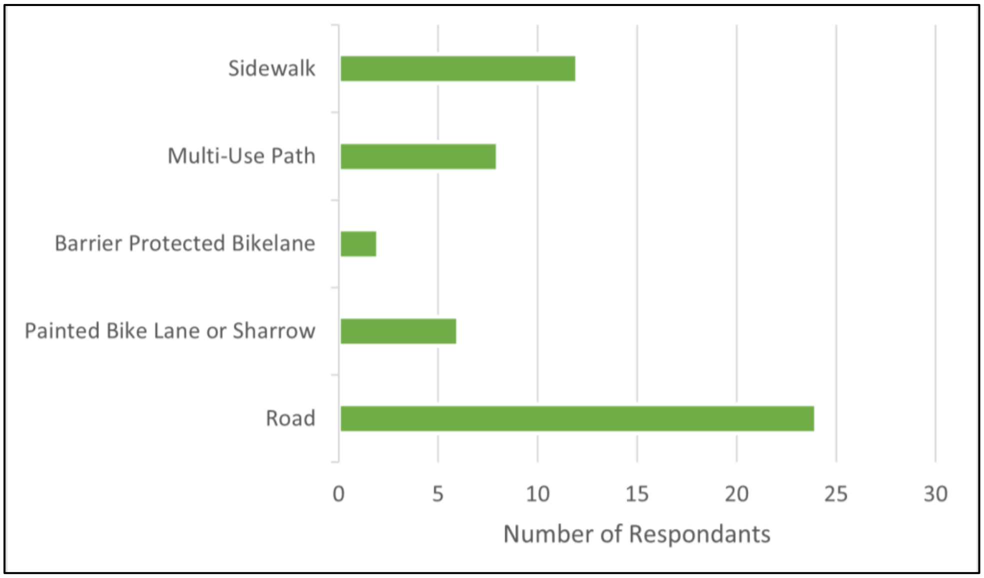


Figure 18: Cycling Infrastructure Deterrent Responses

Figure 19 and Figure 20 show the participants' familiarity with electric bikes and three-wheeled bikes, excluding tricycles for children. There are 23 of the participants are unfamiliar with three-wheeled bikes outside of tricycles, whereas only 5 participants are well familiar with them. It is found that 27 participants are unfamiliar with electric-assisted bicycles, while 8 participants are well familiar with them. This includes 2 cyclists who have used electric-assisted conventional bicycles but not three-wheeled electric bikes.

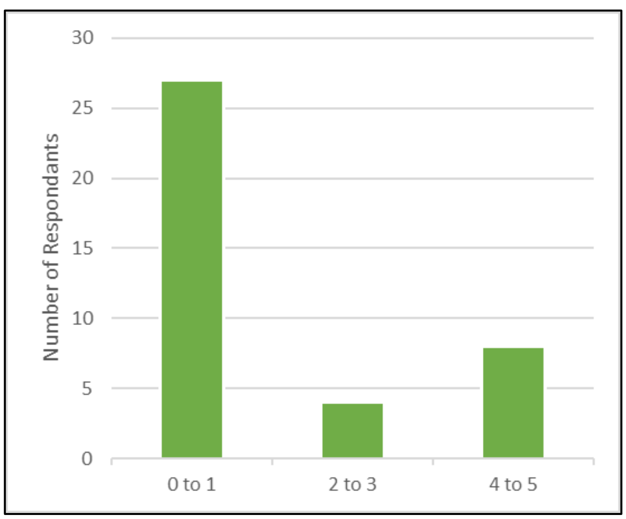


Figure 19: Familiarity with Electric Bikes

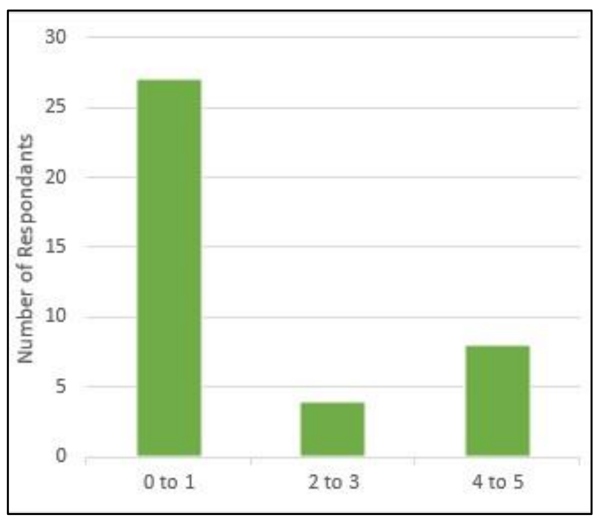


Figure 20: Familiarity with Tricycles

5.1.2 Route & Variable Ratings

The following figures discuss the responses of the Route & Variable section. It is noted that all of the ratings are conducted after riding the ECC Routes. The number of datapoints for each route is not uniform because some of the participants are not able to complete all four routes. The average rating is used to identify the best and worst-performing routes for each variable. Figure 21 shows the travel time and travel distance ratings for each route. Table 8 shows the rating statistics. Participants rated Route 4, on average, to be the longest in terms of time and distance, with an average rating of 4.4, whereas Route 1, on average, is rated the shortest for time, and Route 3 is rated the shortest for distance, with average ratings of 5.6 and 5.8 respectively. For routes 4 and 3, this is expected as the routes are set to be the longest and shortest, respectively. For Route 1, the shorter travel time is due to the higher cycling speeds participants can reach on the route, which, despite having a longer distance, made it competitive with Route 3 in terms of travel time.

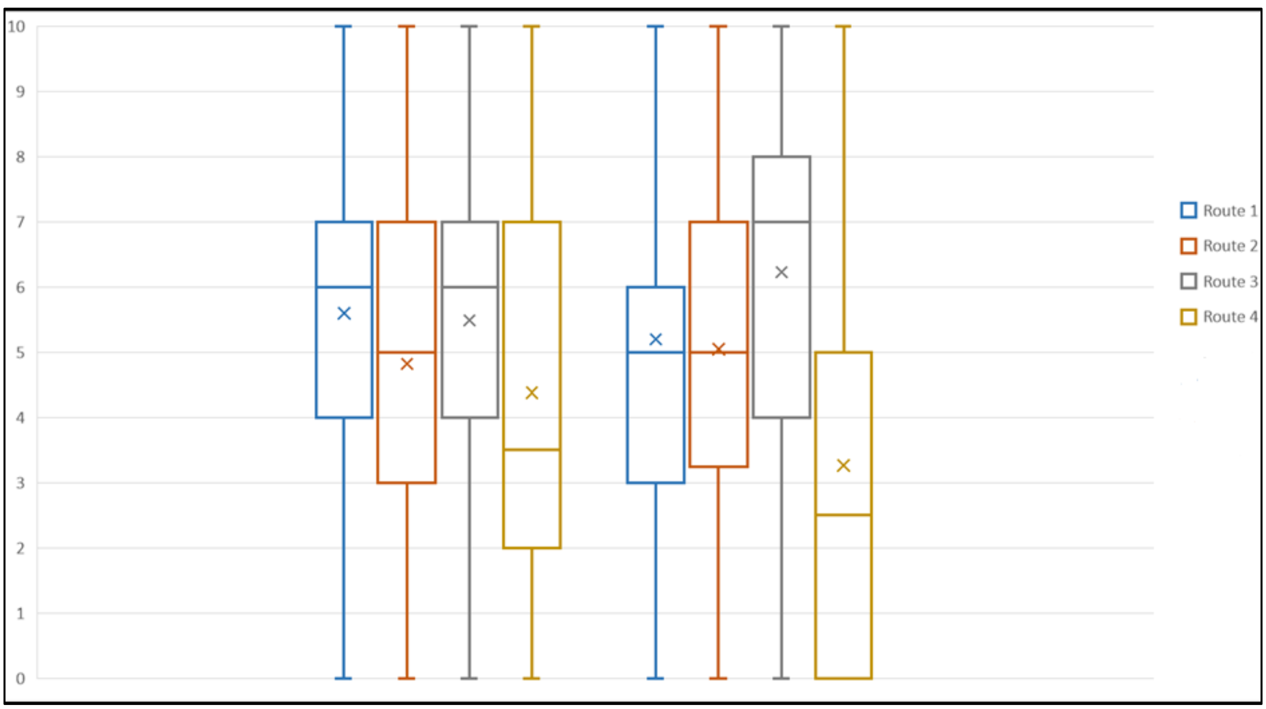


Figure 21: Travel Time [Left] and Travel Distance [Right] Ratings

Table 8: Travel Time and Travel Distance Summary Statistics

Route ID	Count	Minimum	Median	Average	Maximum
Travel Time Rating					
1	35	0	6.0	5.6	10
2	39	0	5.0	4.8	10
3	39	0	6.0	5.5	10

4	34	0	3.5	4.4	10
Travel Distance Rating					
1	35	0	5.0	5.2	10
2	39	0	5.0	5.1	10
3	39	0	6.0	5.8	10
4	34	0	2.5	3.3	10

Figure 22 shows the pavement condition ratings for each route, while Table 9 shows the statistics. Route 2 and route 4 had lower ratings of 5.9 and 6.2 due to sections of the route having more poorly maintained pavement sections compared to routes 1 and 3, both with scores of 6.5. The few very poor spots of pavement on route 2 are enough for its average rating to be poorer than route 4, which had more poor spots along the route. This is evident in the lower minimum ratings for route 2 compared to route 4, which had minimums similar to those of routes 1 and 3.

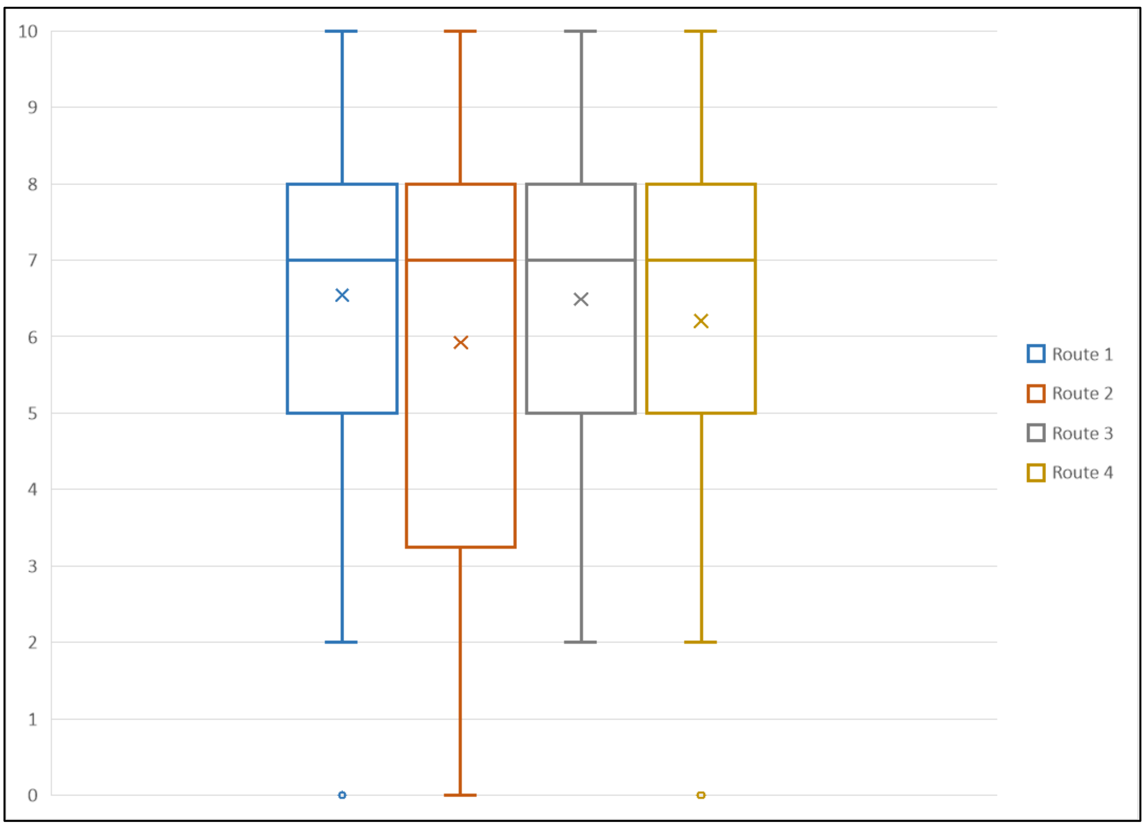


Figure 22: Pavement Condition Ratings

Table 9: Pavement Condition Rating Summary Statistics

Route ID	Count	Minimum	Median	Average	Maximum
1	35	0	7	6.5	10
2	39	0	7	5.9	10
3	39	2	7	6.5	10
4	34	0	7	6.2	10

Figure 23 shows the object visibility and safety ratings of each route, while Table 10 shows the statistics. Route 4, despite having the best average visibility at 8.0, also has the worst average safety rating at 5.9 due to its high traffic volumes and poor pavement conditions. Route 2 had the lowest average visibility at 7.1 due to the presence of tall vegetation and blind spots adjacent to buildings. Route 2 also had the highest average safety rating at 7.1 due to its lower traffic volume and lower use of roads compared to the other routes. Route 3's high pedestrian traffic volume pushed its minimum safety rating close to route 4 despite having the highest median safety rating and its average not being far off from route 2.

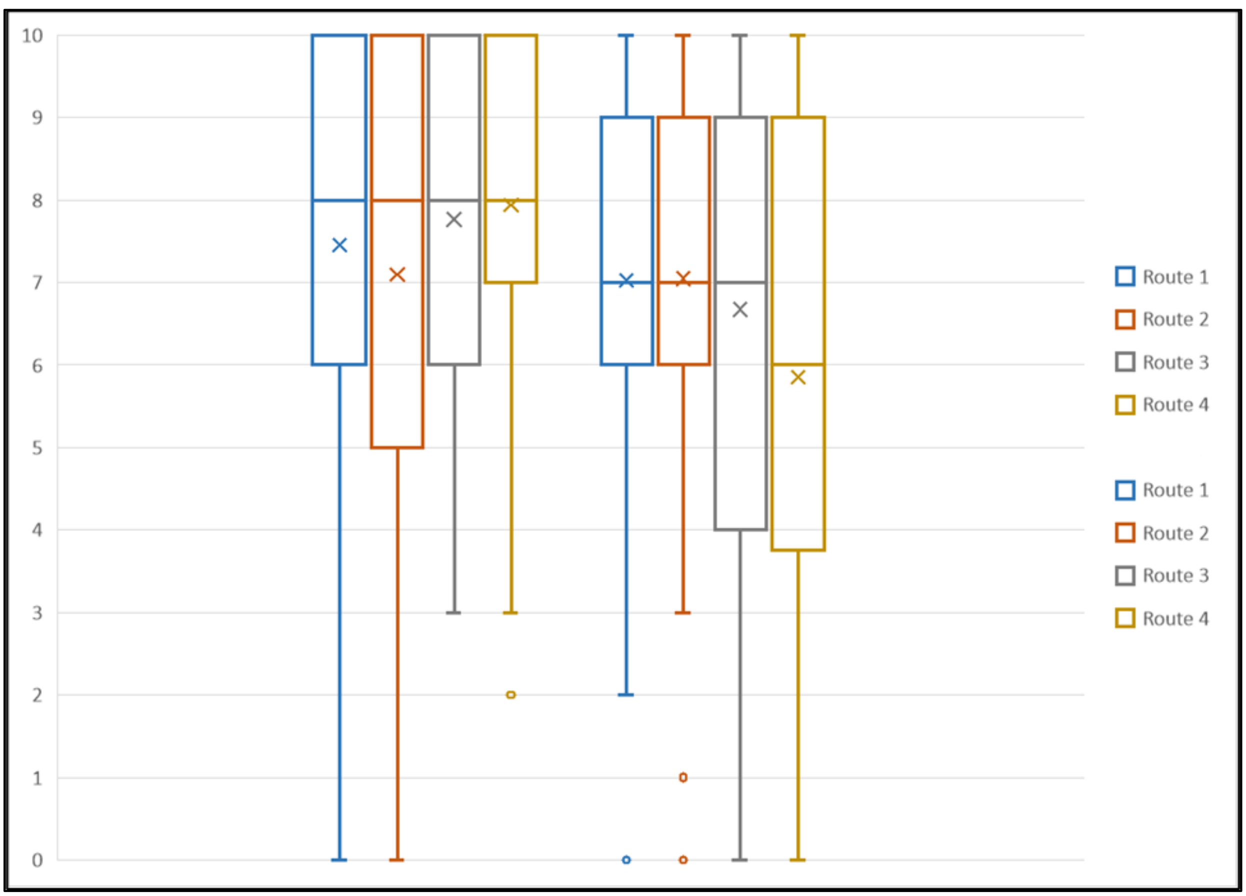


Figure 23: Visibility [Left] and Safety [Right] Ratings

Table 10: Visibility and Safety Rating Summary Statistics

Route ID	Count	Minimum	Median	Average	Maximum
Visibility Rating					
1	35	0	8	7.5	10
2	39	0	8	7.1	10
3	39	3	8	7.8	10
4	34	2	8	8.0	10
Safety Rating					
1	35	0	7	7.0	10
2	39	0	7	7.1	10
3	38	0	7.5	6.8	10
4	34	0	6	5.9	10

Figure 24 shows the comfort and enjoyment ratings, while Table 11 shows the statistics. Route 2 had the highest average comfort rating at 6.4, with routes 1 and 3 close behind at 6.3 and 6.2, respectively. Route 4 had the lowest average comfort rating at 5.7 due to its higher traffic volume and poor pavement. Route 4 ended up with the highest average enjoyment rating at 6.9 due to its ability to cycle at higher speeds and lower pedestrian traffic. Route 1 is similar in terms of its average enjoyment rating at 6.8 but with a higher maximum enjoyment rating due to similar reasons, although it benefitted more from its better pavement condition. Route 2 had the lowest enjoyment rating at 6.6 due to the spots of very poor pavement disrupting the experience while also reducing the speed travelled at many points along the route.

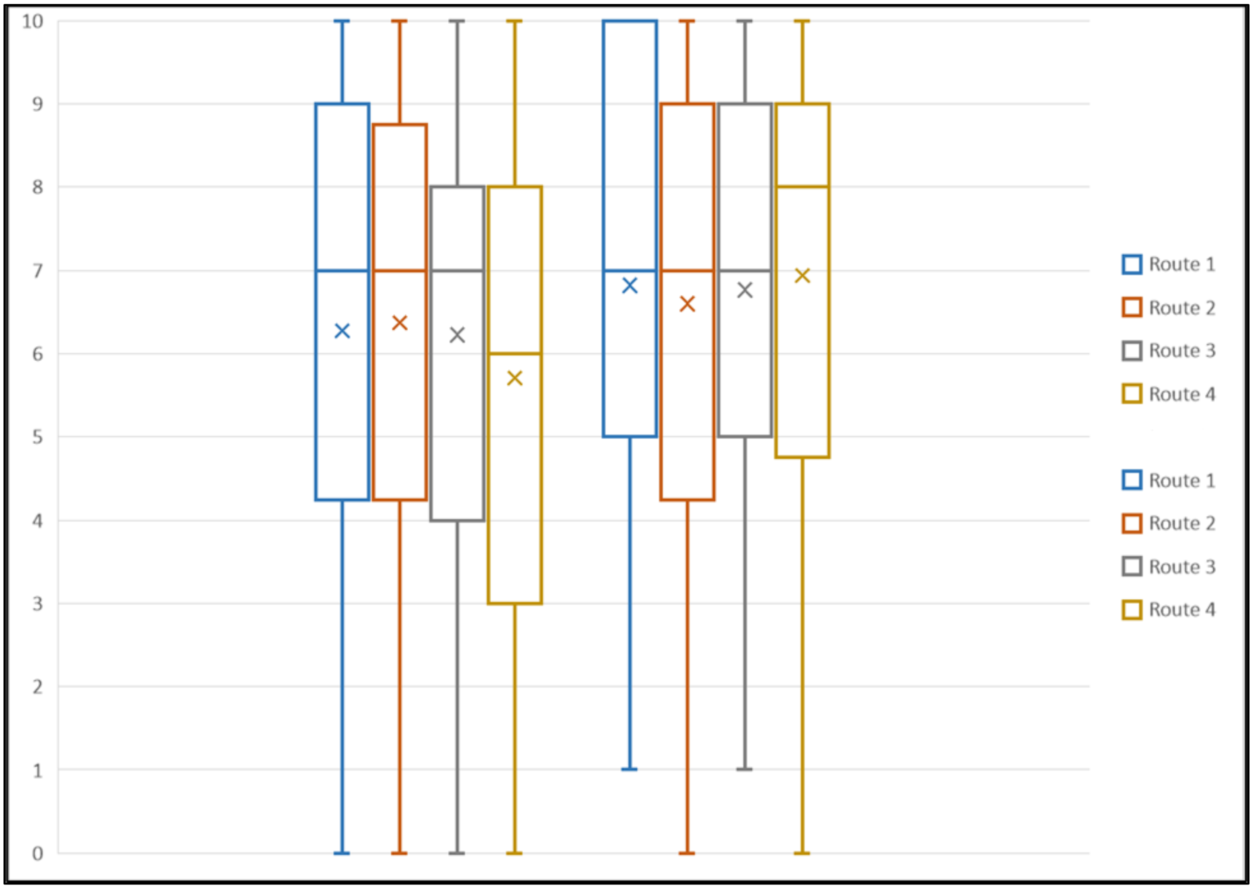


Figure 24: Comfort [Left] and Enjoyment [Right] Ratings

Table 11: Comfort and Enjoyment Rating Summary Statistics

Route ID	Count	Minimum	Median	Average	Maximum
Comfort Rating					
1	36	0	7	6.3	10
2	39	0	7	6.4	10
3	39	0	7	6.2	10
4	34	0	6	5.7	10
Enjoyment Rating					
1	34	1	7	6.8	10
2	39	0	7	6.6	10
3	39	1	7	6.8	10
4	34	0	8	6.9	10

Figure 25 shows the overall route attractiveness rating, while Table 12 shows the statistics. This question allowed respondents to rate the route by considering not only the variables evaluated throughout the entire survey but also the variables that may not have been measured in this study. Route 3 had the highest average overall route attractiveness rating at 7.4, followed by route 4 at

7.3, with routes 1 and 2 having the lowest average ratings at 6.9 and 6.7, respectively. This can be due to the lack of destinations along the route as routes 3 and 4 pass by a more significant number of establishments such as malls, stores and services that the participants may want to access compared to routes 1 and 2, which have a lower number of establishments. This makes the routes more attractive to use despite their challenges and lower ratings in some of the variables surveyed. These establishments also benefit well from the use of an ECC due to the ability to purchase or drop off goods to and from these establishments while being easily accessible by ECCs.

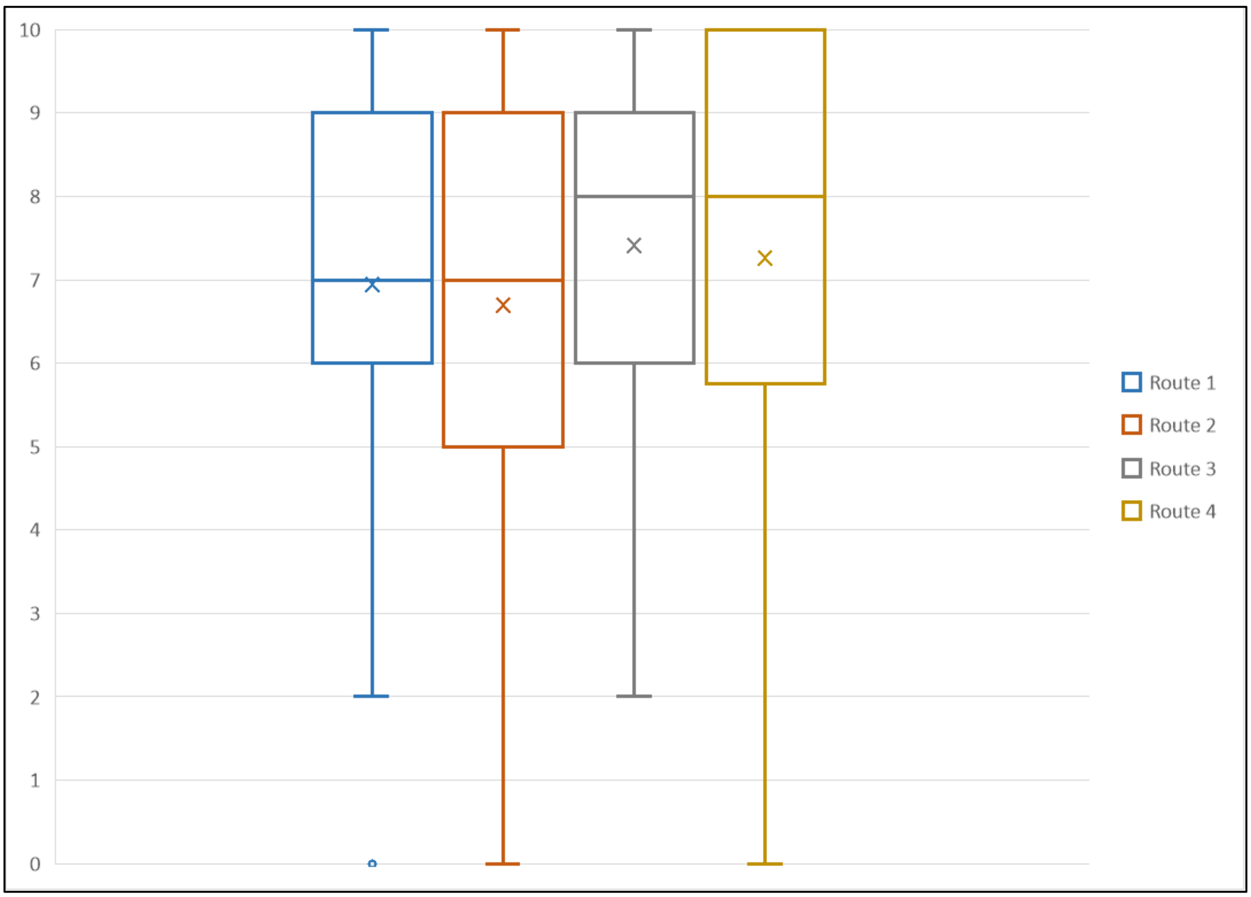


Figure 25: Route Attractiveness Rating

Table 12: Route Attractiveness Rating Summary Statistics

Route ID	Count	Minimum	Median	Average	Maximum
1	35	0	7	6.9	10
2	39	0	7	6.7	10
3	39	2	8	7.4	10
4	34	0	8	7.3	10

Route 1 had the most favourable average ratings for travel time and pavement condition. It is not the least favourable for any of the ratings. Route 2 had the most favourable average ratings for safety and comfort, and the least favourable average ratings for pavement condition, visibility, enjoyment and the overall route. Route 3 had the most favourable average ratings for the travel distance and the overall route. It is not the least favourable for any of the ratings. Route 4 had the most favourable average ratings for visibility and enjoyment, and the least favourable average ratings for travel time, travel distance, safety and comfort.

5.1.3 Route Rankings

The previous rating results discussed the participant's ratings of each route based on a cycling variable. This section discusses the results where each route is compared with another route, additional pairwise questions ask participants to rank the variables, but these results are presented later in chapter 6.1. The participant has to choose which one of the two routes performed better in a particular cycling variable. This involves pairwise comparisons of all possible pairs of the four routes, with the participant only completing the pairs where they had ridden both routes. The rankings for the routes are determined by computing the proportion of the route being chosen and the number of times the route could have been selected from the route ranking section of Part 2 of the survey. This is counted for each variable used to rank the routes as seen in the survey questions in Appendix C.

Table 13 shows the route ranking results based on the 11 route variables asked in the survey. The proportions are based on the number of times a route is picked for a variable and the total number of times that route could have been picked for that variable. Route 1 is ranked the best route for all of the variables by a significant margin. Route 3 is ranked as the second-best route, with 8 of the variables being ranked second; route 2 is third, with 7 of the variables ranked third; and route 4 is the worst route, with seven variables ranked last. Route 2 ranked last in cycling infrastructure, visibility and junctions due to the use of narrow and congested multi-use paths with some poorly maintained as well as the high number of turns on the route and the presence of large foliage close to the intersections on the route. Route 3 ranked last in sightlines due to its use of pathways with tight, sharp turns that make it harder to see oncoming pedestrians. Route 4 ranked last in various variables due to the route being set as the longest route and due to the poor pavement and high vehicle traffic volume along a significant length of the route.

Table 13: Route Chosen Proportion

Variable	Route 1	Route 2	Route 3	Route 4
Travel Time	63%	49%	49%	38%
Travel Distance	67%	43%	48%	41%
Pavement	63%	45%	55%	37%
Bike Infrastructure	60%	43%	53%	44%
Junctions	69%	40%	47%	44%
Collision Risk	70%	49%	42%	39%
Object Frequency	71%	45%	51%	33%
Visibility	63%	43%	43%	51%
Sightlines	68%	43%	42%	48%
Discomfort	61%	42%	56%	41%
Enjoyment	67%	43%	53%	38%

Overall, while Route 1 is ranked the best in all categories, in the survey ratings it only ranked the best in 2 categories and placed either 2nd or 3rd best of the four routes for the other categories. The device output results are discussed in the next section to see if this pattern is accurate.

5.2 Device Output

The device output results include GPS data, Gyroscope data and Video data. The GPS route results are obtained from the Strava app via a GPS-connected smartphone and through a Garmin 530 GPS. The data is processed through ArcGIS Pro. The gyroscope data is obtained from the Wit Motion Gyroscope and is processed in an excel spreadsheet. The video data is obtained from the Go Pro Camera and is processed through Adobe Premiere Pro and time-matched with the processed gyroscope output.

5.2.1 GPS

The GPS data is used as inputs for the observed average travel time, distance and speed of each participant on each route and the speed category proportions by route. It is used to verify the number of turns conducted, the number of intersections passed, and the percentage of cycling infrastructure travelled per route in each direction. Figure 26 shows the observed travel time results in minutes for each participant on each route. For travel time, a higher value indicates a poorer-performing route. Table 14 shows the summary statistics for the travel time. The x-mark represents the median, while the line across the boxplot represents the average. Route 4 had the longest travel time, while Route 3 had the shortest travel time. This is expected because Route 3 is created as the shortest of the four routes compared to Route 4, which is intended to be the longest of the four routes. This aligns with the expected travel time trend outputted from Google Maps in Table 4.

Despite being designed as the second longest route, participants on Route 1 tend to record lower travel times compared to those on Route 3, despite being developed as the second shortest route with an average travel time similar to Route 1.

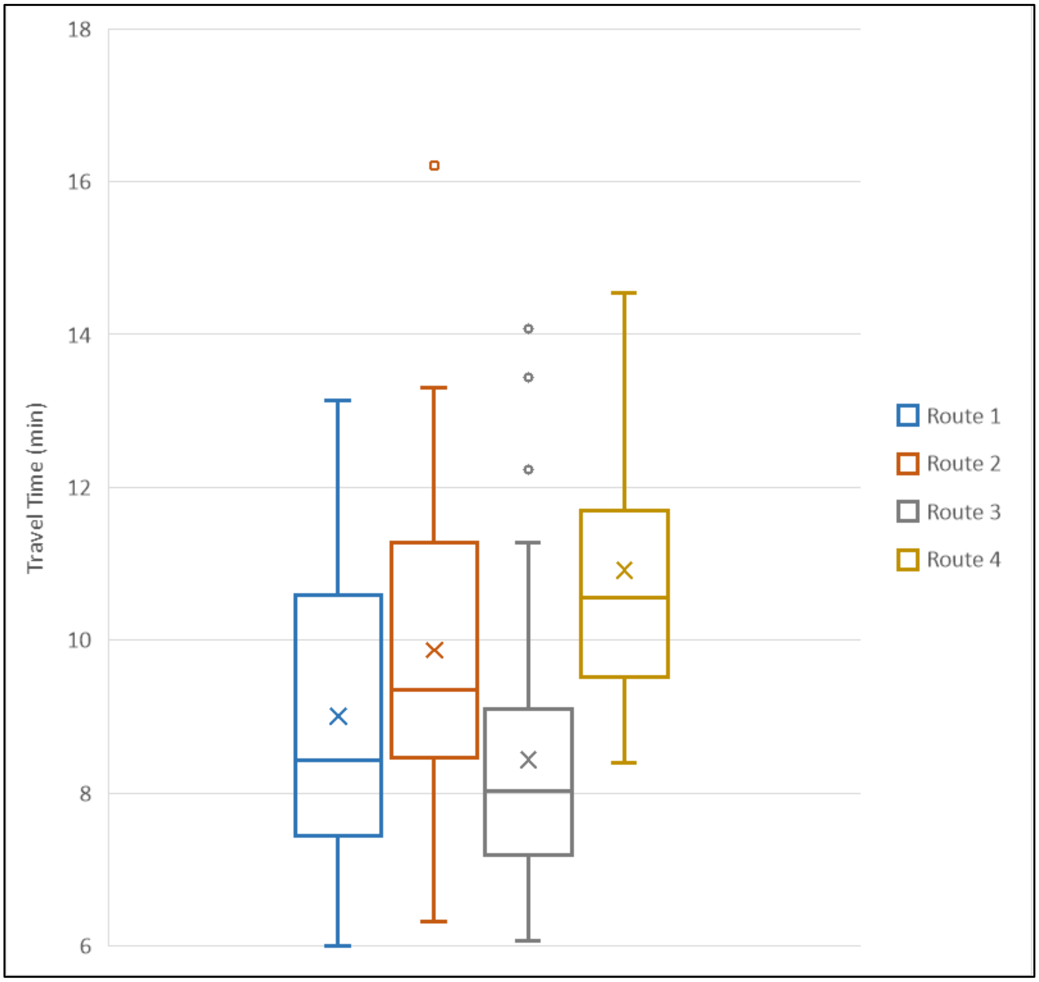


Figure 26: Observed Travel Time Results

Table 14: Travel Time (Minutes) Summary Statistics

Route ID	Count	Minimum	Median	Average	Maximum	Standard Deviation
1	36	6.0	8.8	9.0	13.1	1.8
2	39	6.3	9.4	9.8	16.2	2.0
3	39	6.1	8.0	8.4	14.1	1.9
4	34	8.4	10.6	10.9	14.5	1.6

The travel distance results in Figure 27 and Table 15 show that the distances travelled by each participant are close to the original route length. For travel distance, a higher value indicates a poorer-performing route. This is from longest distance to shortest: Route 4, Route 1, Route 2 and

Route 3. Compared to the travel time results, route 2, with an average distance of 1.6 km while being shorter than Route 1 at 1.7 km, yielded an average travel time greater than Route 1 at 9.4 minutes compared to 8.8 minutes. Route 1 had longer straight segments with fewer turns needed to be made along the route, which reduced the time spent stopping and turning compared to route two, which had shorter straight segments and more stops and turns to be made. Since the routes have a fixed origin and destination, the travel distance is fixed, and it is expected that the distances do not differ significantly. Yet, there are cases where this occurred. Route 4 in Figure 27 shows a lower extremum of 1.6 km despite the route being 2.1 km long and the majority of participants having distances of ±100 m. Viewing the GPS data points in ArcGIS Pro showed that the participant took a shortcut along the route. This participant's verbal reasoning for choosing this shortcut is discussed in a later section as despite being the only participant that took such a noticeable shortcut, the reasoning does come up a couple of times by the participants.

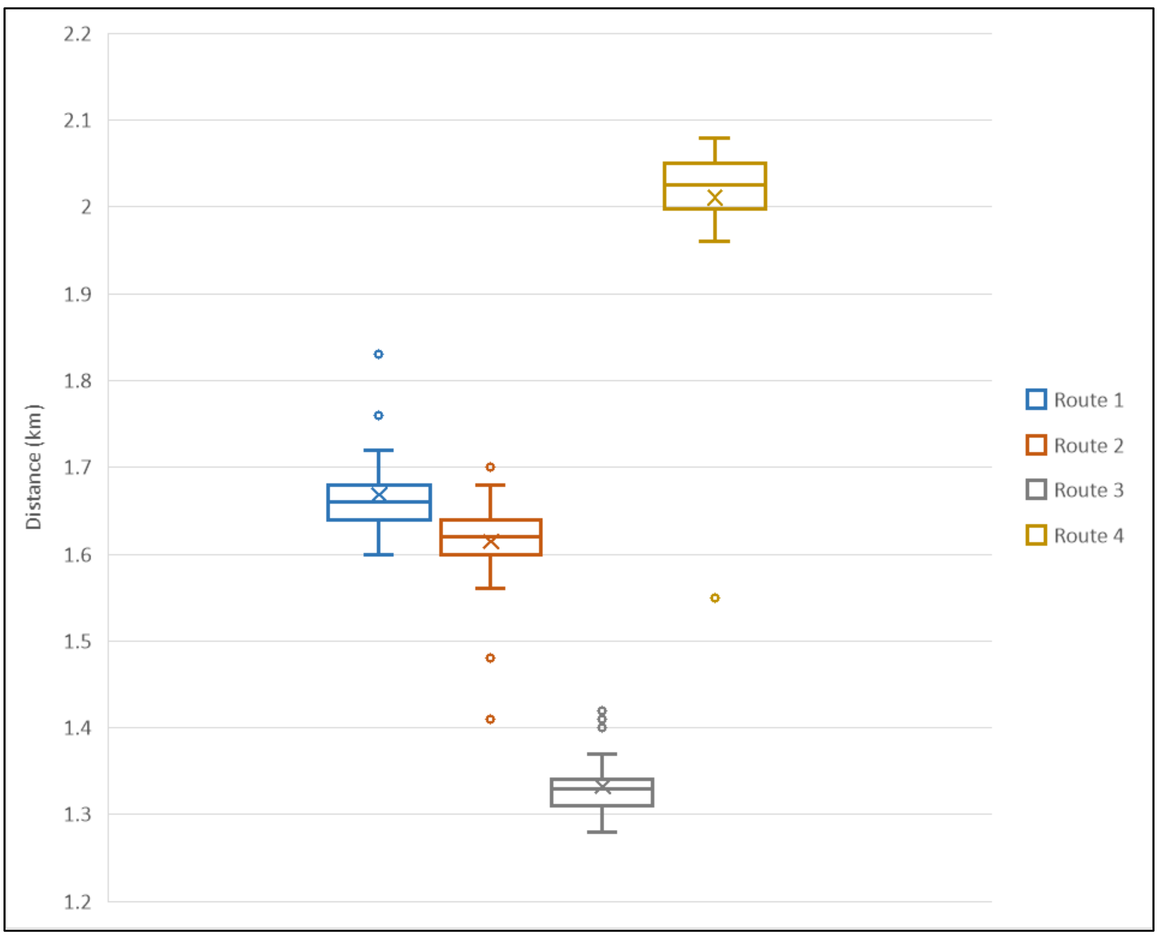


Figure 27: Observed Travel Distance Results

Table 15: Travel Distance Summary Statistics

Route ID	Count	Minimum	Median	Average	Maximum	Standard Deviation
1	36	1.6	1.7	1.7	1.8	0.04
2	39	1.4	1.6	1.6	1.7	0.05
3	39	1.3	1.3	1.3	1.4	0.03
4	34	1.6	2.0	2.0	2.1	0.09

The breakdown of the route infrastructure by proportional distance for each route is shown in Figure 28. For the route infrastructure results, a lower value indicates a poorer-performing route. The infrastructure is demonstrated for both directions of travel along the route. The figure shows that there are slight changes in the route infrastructure proportions depending on the direction of the route that is being used. However, the overall infrastructure proportions remain consistent regardless of direction. Route 4 used the multi-use paths the least but also road on a noticeable portion of bike lanes. This resulted in fewer unmarked roads being used compared to Route 1, which used unmarked roads the most, and its overall bike infrastructure usage is the lowest. Route 2 and route 3 have identical infrastructure proportions, with Route 2 having two sections of multi-use path and two sections of road, while Route 3 had 1 section of multi-use path and 1 section of road, as seen in Figure 5 and Figure 6 previously.

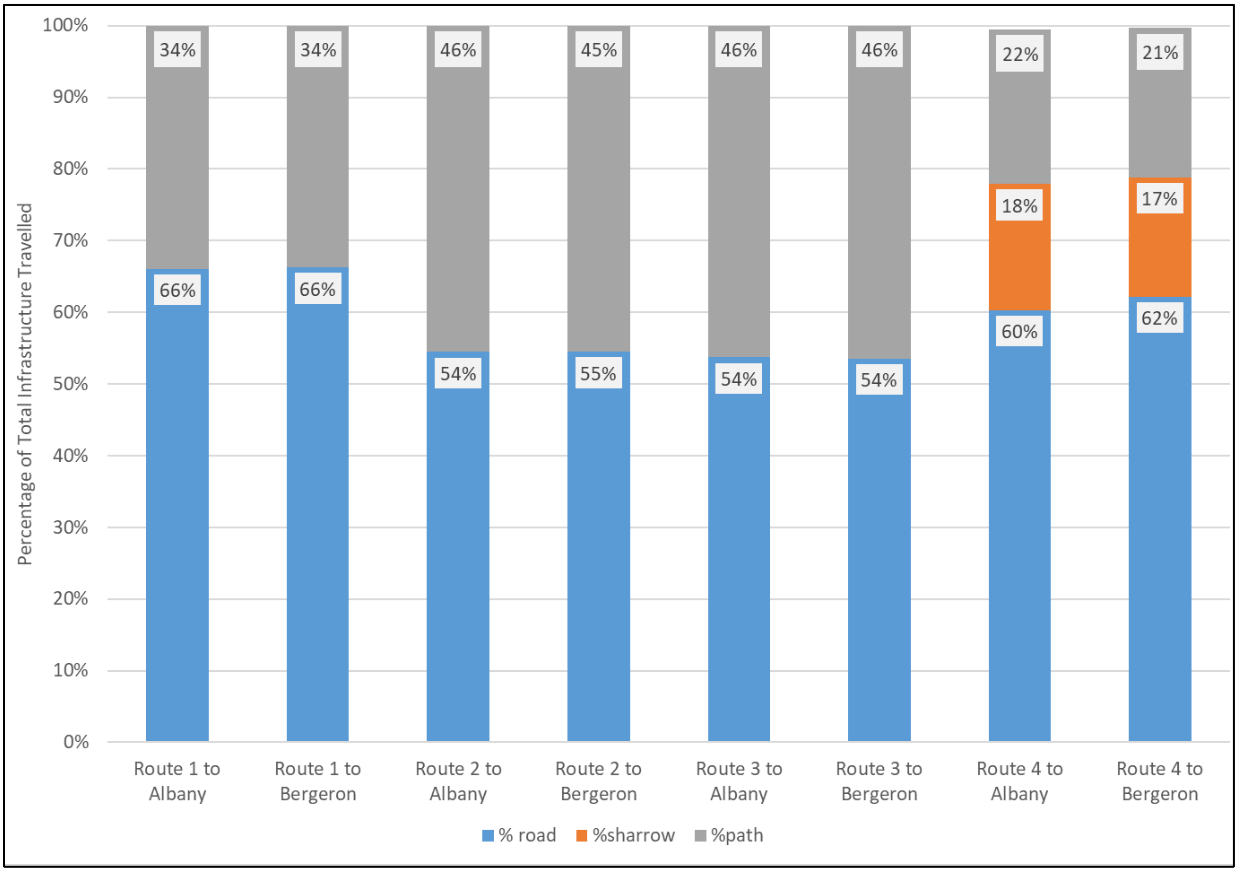


Figure 28: Route Infrastructure Proportion by Route and Direction

The proportions for route 4 are computed using a weighted average of the participant's alternate routes from the field study. A few participants made detours along the route around the Vanier Lane parking lot, as shown in Figure 29. Participants are given the option to either use the roads on the perimeter of the lot or enter the parking lot and cut through it. Both measures resulted in similar travel distances, and the infrastructure proportions did not noticeably differ, as seen in Figure A10 in Appendix A, except for the case previously brought up with the participant travelling 0.45 km less on route 4. Their route around the parking lot is to avoid a large portion of the designated route and to go directly back on the main road, as seen by the straight dark blue line in the upper left corner of the figure. Figure A10 in Appendix A also shows that their cycling infrastructure used to be 69% road and 31% multi-use path, avoiding the sharrow entirely. This route uses the most roads, and the lowest cycling infrastructure compared to any of the predetermined routes.

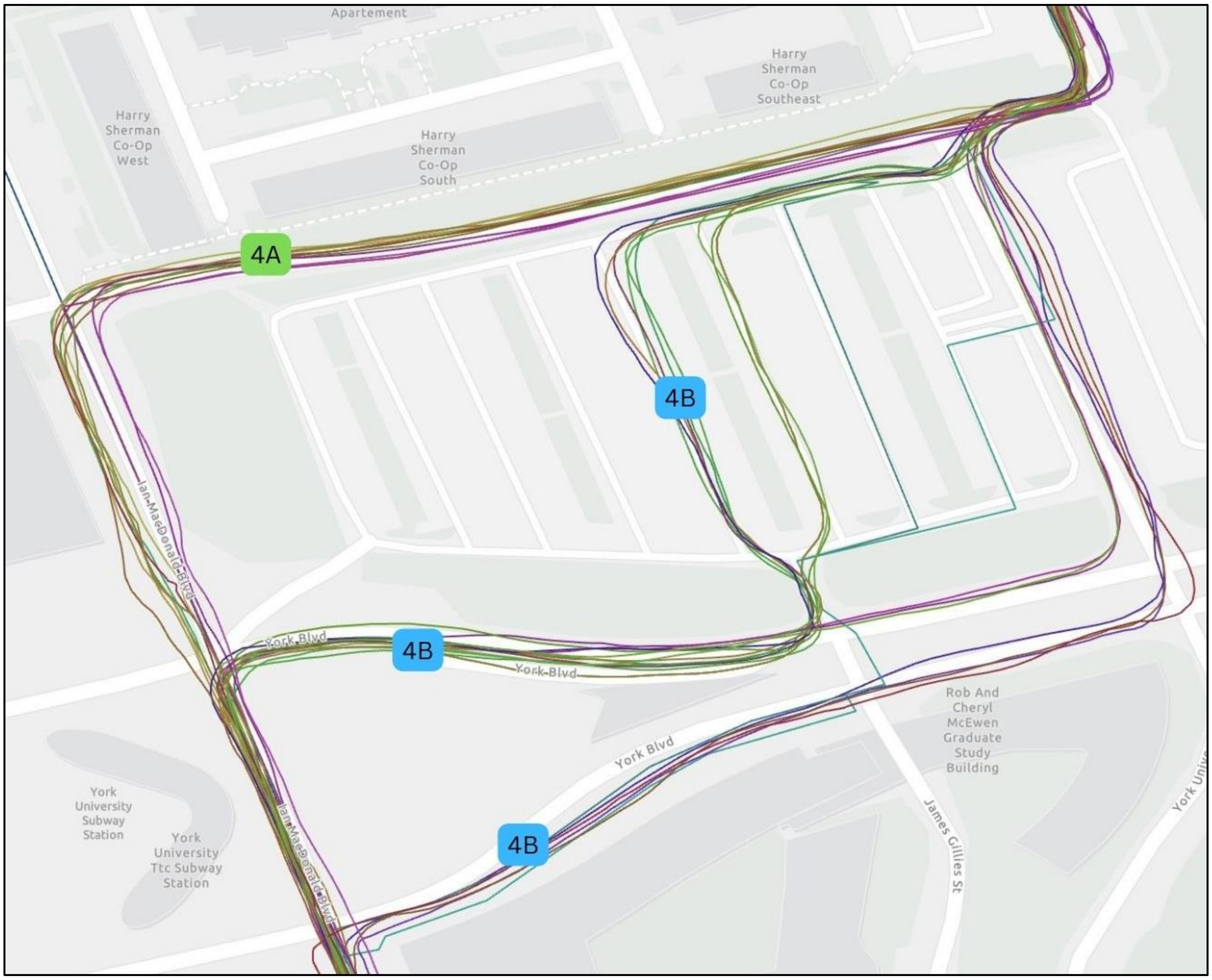


Figure 29: Participants Routes Through the Vanier Lane Parking Lot

5.2.2 Speed

For average speed, a lower value indicates a poorer-performing route. The average speed results shown in Figure 30 and summarized in Table 16 show that participants on Route 1 can travel at a higher average speed of 13.0 km/h, followed by Route 4 slightly behind at 12.6 km/h. These two routes primarily consisted of straight segments of road or shared bike lanes that gave participants more space to cycle at a high speed with less interaction with pedestrian traffic. Route 3 had the lowest average speed at 11.0 km/h, followed by Route 2 at 11.2 km/h due to their use of multi-use paths, which are shared with pedestrians, affecting the participant's ability to safely maintain a high cycling speed. The higher speed on Route 1 is why it took participants less time to complete the route compared to Route 2 despite both having similar travel distances.

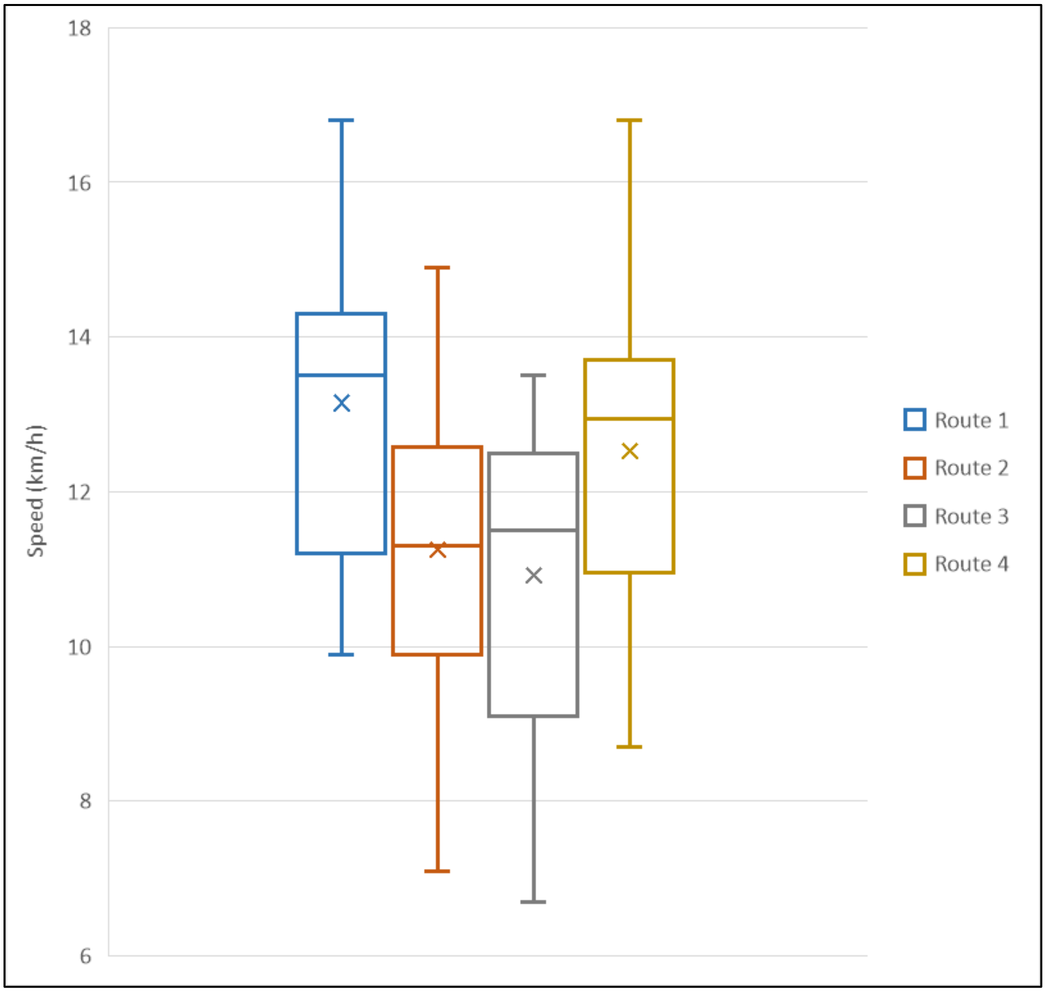


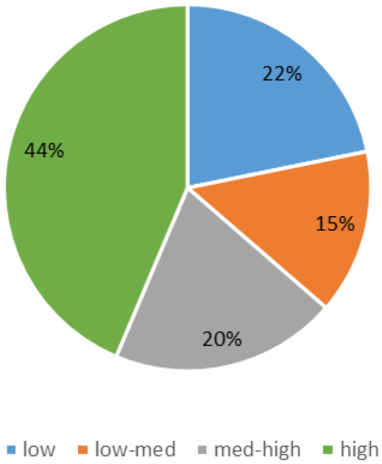
Figure 30: Average Speed Results

Table 16: Average Speed Summary Statistics

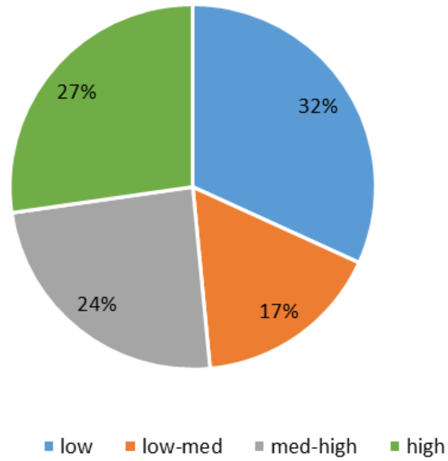
Route ID	Count	Minimum	Median	Average	Maximum	Standard Deviation
1	36	9.2	13.2	13.0	16.8	2.0
2	39	7.1	11.3	11.2	14.9	1.8
3	39	6.7	11.6	11.0	13.5	1.9
4	34	8.7	13.0	12.6	16.8	1.9

One way of categorizing participants is to assign a speed category to the participant based on not only their average speed on the routes but also responses that divide the participant pool between enthusiast class cyclists and leisure class cyclists. This allows for data from all of the variables to be considered, developing an overall picture of how these types of cyclists approach the use of an ECC. This is used in chapter 6.1 where the categories allow identifying the changes in variable weights among the two participant groups. Four-speed categories are developed by adding or subtracting one or two standard deviations depending on the category, applying them to each route direction, and taking the average of each category's values to apply to all routes. For the low category speed, two standard deviations are subtracted, resulting in a speed requirement of less than 10.1 km/h. For the low-medium (low-med) category, one standard deviation is subtracted with a range of between 10.1 km/h and 12.0 km/h. The medium-high (med-high) category had one standard deviation added to it, with a range between 12.0 km/h and 13.9 km/h. Lastly, the high category had two standard deviations added to it with a speed of greater than 13.9 km/h. Figures 29a to 29d show the route proportion of each speed category, with Routes 1 and 4 comprising a more significant proportion of the Medium-High and High-speed categories, whereas Routes 2 and 3 comprise a more substantial proportion of the Low and Low-Medium speed categories. Figures 31a to 31d show the speed category proportion by each route. Over 40% of the participants on routes 1 and 4 had a high average speed category compared to 27% of the participants on routes 2 and 3. Less than 22% of the participants on routes 1 and 4 had a low average speed compared to over 32% of participants on routes 2 and 3. Participants with 2 or more routes with speeds within the med-high or high categories are assigned as enthusiast cyclists whereas participants with 2 or more routes within the med-low and low-speed categories are assigned as leisure cyclists.

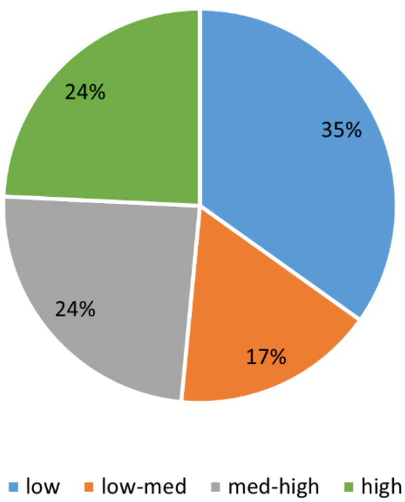
At the moderate speed levels, assigning the participant to one of two categories is assisted using a clustering chart that groups participants into one of two average speed clusters as the assignment becomes more subjective for moderate speeds. The categories were visualized using a cluster chart in Microsoft PowerBi to identify the pattern between the cyclists' average speed and their overall route attractiveness rating. The cluster chart is computed using a k-means algorithm which allows for a simple interpretation of the clusters produced (QuantHub, 2022) (Wongoutong, 2024). Figure A11 in Appendix A shows the cluster chart using the overall route attractiveness rating as the independent variable and the average speed which was used to form the initial categories as the dependent variable. Two clusters which visually represent the high and low-speed categories were created. The cluster with the high-speed category represents the enthusiast cyclists which shows that the participants who rated the routes with a higher rating tended to have higher average speeds whereas the cluster with the low-speed category shows that participants who rated the routes with a lower rating had a lower average speed. The split between clusters is located around the ratings from 6 to 7. This is where the average route attractiveness ratings for each route tended to fall between. The values in each cluster have an Object ID (previously Participant ID) which is used to modify the assignment of participants to one of the two categories.



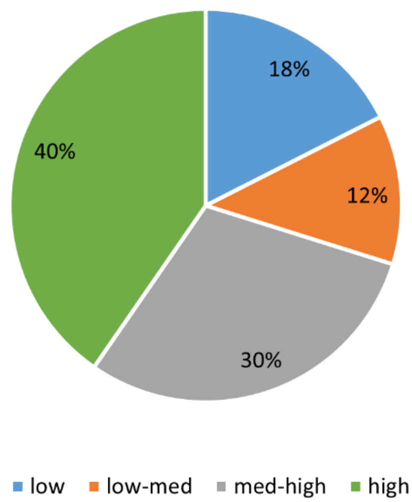
[a]: Route 1-speed proportion



[b]: Route 2-speed proportion



[c]: Route 3-speed proportion



[d]: Route 4-speed proportion

Figure 31: Speed Category Proportion

5.2.3 Gyroscope

The comfort results from the gyroscope are presented as discomfort results, where the higher the value, the more discomforting the experience is for the participant. The results are computed from the 3-axis acceleration using equation 8, following ISO 2631 about mechanical vibration and shock.

$$aw_v = \sqrt{{aw_x}^2 + {aw_y}^2 + {aw_z}^2} \qquad (11)$$

Where aw_v is the cycling vibration in m/s^2, and aw_x, aw_y and aw_z are the acceleration in the x-axis, y-axis, and z-axis, respectively.

This equation computes one instance of cycling vibration. The instances are summed as the total discomfort for each route. A lower cycling vibration indicates a lower discomfort and a more comfortable route. Due to the shape of the gyroscope and the need to access the device while mounted, the gyroscope is mounted upright with the x-axis pointing in the typical direction of the z-axis (up and down) with the z-axis in the direction of the x-axis (side to side) and the y-axis in the front to back direction. This is mounted in the same orientation for all participants.

The results in Figure 32 and Table 17 show that Route 4 had the highest average discomfort at 753.3 m/s^2, followed by Route 2 at 744.9 m/s^2. The discomfort on Route 4 is due to several instances of poor pavement, which resulted in higher vibrations and, thus, higher discomfort, whereas the discomfort on route 2 is amplified by a few sections along the route. One such example included a participant riding uphill over many distresses diagonally rather than straight through, which resulted in higher readings. Some of the participants' cycling behaviours on route two also influenced their high discomfort. Route 3 had the lowest discomfort at 578.6 m/s^2 compared with route 1 in between, with a discomfort of 664.7 m/s^2. While route 1 had several extreme discomfort results similar to route 4, its average discomfort is lower due to the route's wider roads and lower number of moving and parked vehicles, allowing the participant to feel more comfortable cycling and in their ability to navigate around pavement distresses instead of having to ride through the distress. Also, the pavement on route 1 tended to be in better condition than on route 4, with distresses that mainly occurred next to the curb of the road and not through the center. The variability of the results is more significant for route one because some participants are either uncomfortable or unfamiliar with trying to avoid pavement distresses when cycling, leading them to stay closer to the curb where the distresses occurred rather than in the center of the lane.

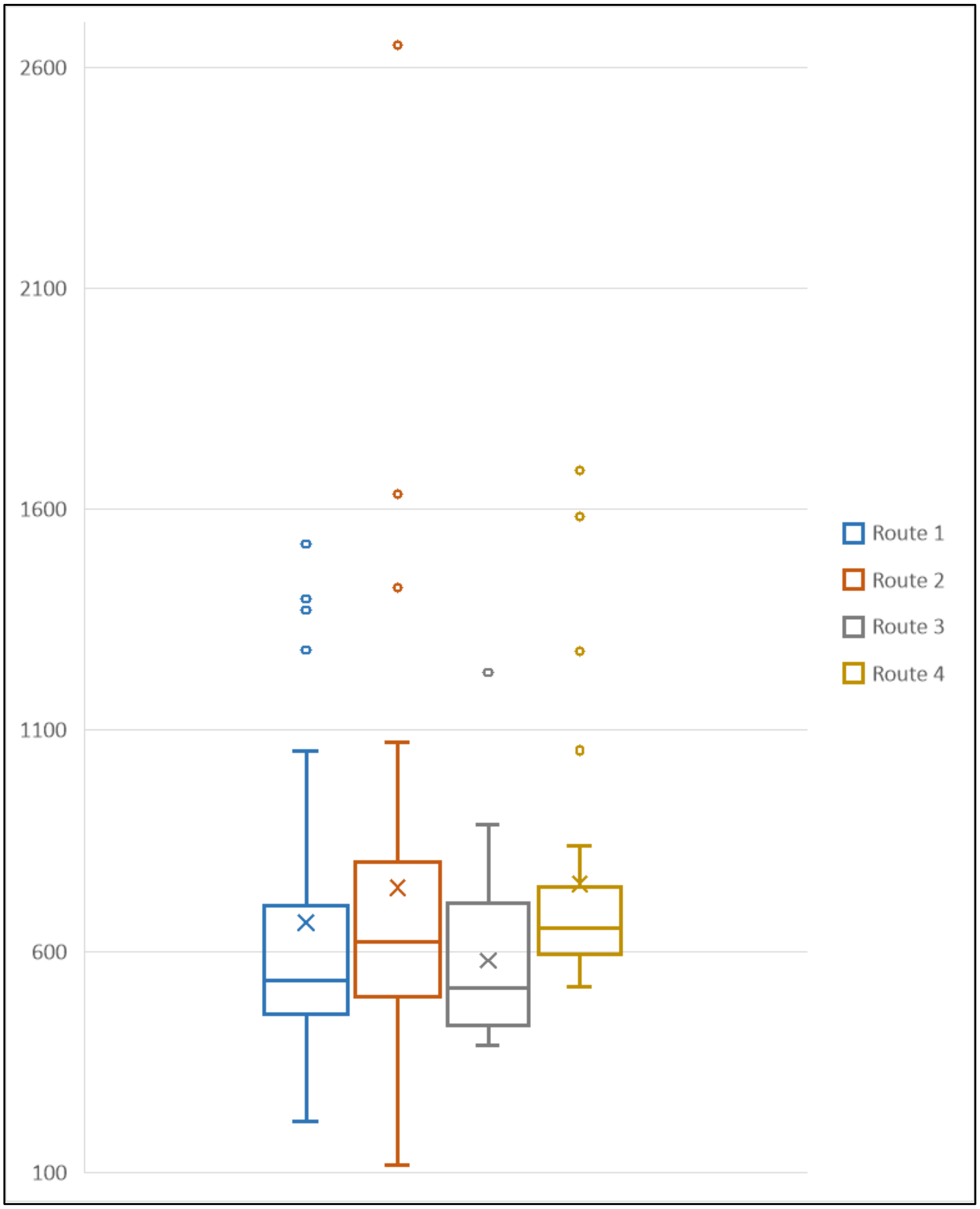


Figure 32: Discomfort Results

Table 17: Discomfort Results Summary Statistics

Route ID	Count	Minimum	Median	Average	Maximum
1	29	215.9	534.8	664.7	1523
2	35	116.3	622.4	744.9	2651
3	31	388.2	516.3	578.6	1230
4	28	518.9	652.5	753.3	1687

By plotting the gyroscope data and comparing it with the video data of the route by matching the times each is collected, it is possible to assign one or more vibration results from the graph to one or more distress(es) on a section of the route. For example, a part of a route with a pothole or sharp bump shows a vibration reading with a very high amplitude but for a shorter period, whereas a part of the route with alligator cracking shows a series of noticeably higher amplitudes for a more extended period. The vibration results from the gyroscope are recorded for every half second, whereas the video timecodes are for every second. The average of each half-second result is computed to convert the gyroscope data in terms of seconds. It should be noted that the gyroscope's software's internal clock is 5 minutes behind the GoPro camera's time, which is synced with the real-world time that is considered when matching the events. The categories for the distresses, referred to here as bumps, are based on the amplitude of the vibration. Among all the results, the amplitudes travelling on sections of the routes are between 0.8 to 1.2, with the axis preset at 1.0 by the gyroscope. This is the typical range or amplitude when not travelling over central pavement distresses. The categories of the bumps are broken up into quartiles greater or less than one at intervals of ±0.2. For small bumps, this would be an amplitude that is between 0.6 to 0.8 or 1.2 to 1.4. Larger bumps are to occur if the amplitude is greater than 1.4 or less than 0.6.

Figure 33 and Figure 34 show the number of small and large bumps the participants experienced along the route. Table 18 and Table 19 summarize the results. As previously mentioned, technical challenges with the gyroscope resulted in 4 of the participant's data not being recorded correctly. Route 4 had the most significant average number of small bumps at 51, whereas Route 3 had the lowest average number of small bumps at 31. For the large bumps, route 4 had the most significant average number of large bumps, whereas route 3 had the lowest average number of large bumps at 7. Routes 1 and 2 are slightly less than route 4 at 12 each. Many of the bumps included artificial depressions from sewer covers. These covers sank into the ground much deeper than the rest of the pavement and are commonly seen on the multi-use pathways along each route. The tactile pavement at the end of the multi-use path on Route 2 is another artificial feature that resulted in several bumps being recorded by the gyroscope as the pavement presents a rough surface that, when it comes into contact, vibrates the ECC in all directions to deaccelerate it. Table A2 in Appendix A has a location of pavement distresses along all four routes that are responsible for causing several significant vibrations, including man-made features. Each route has a few outliers, with readings significantly more substantial than the typical range of the readings. This can be attributed to how the participant navigated the bump and how straight the participant is moving on certain sections of the route. It is found that the outliers are the result of 5 participants with IDs

05A, 05B, 07C, 08B and 08C. The outlier participants had average speeds within the medium-high and high-speed categories. There are 3 of 5 outlier participants in the enthusiast cyclist category with experiences cycling in rain, snow, and cold weather and cycled for 3 or more days per week. Also, they rated the routes above average in terms of safety. Analyzing the video recordings found that these outlier participants took on the locations of significant vibrations from Table A2 at high speeds which resulted in stronger vibrations. This means that the outliers are caused by cycling at a high speed over the distress without attempting to avoid the distress or slowing down when taking the distress head-on. Participants who experienced a higher number of bumps made minimal effort to take measures to avoid or reduce the effect of the bump on their discomfort.

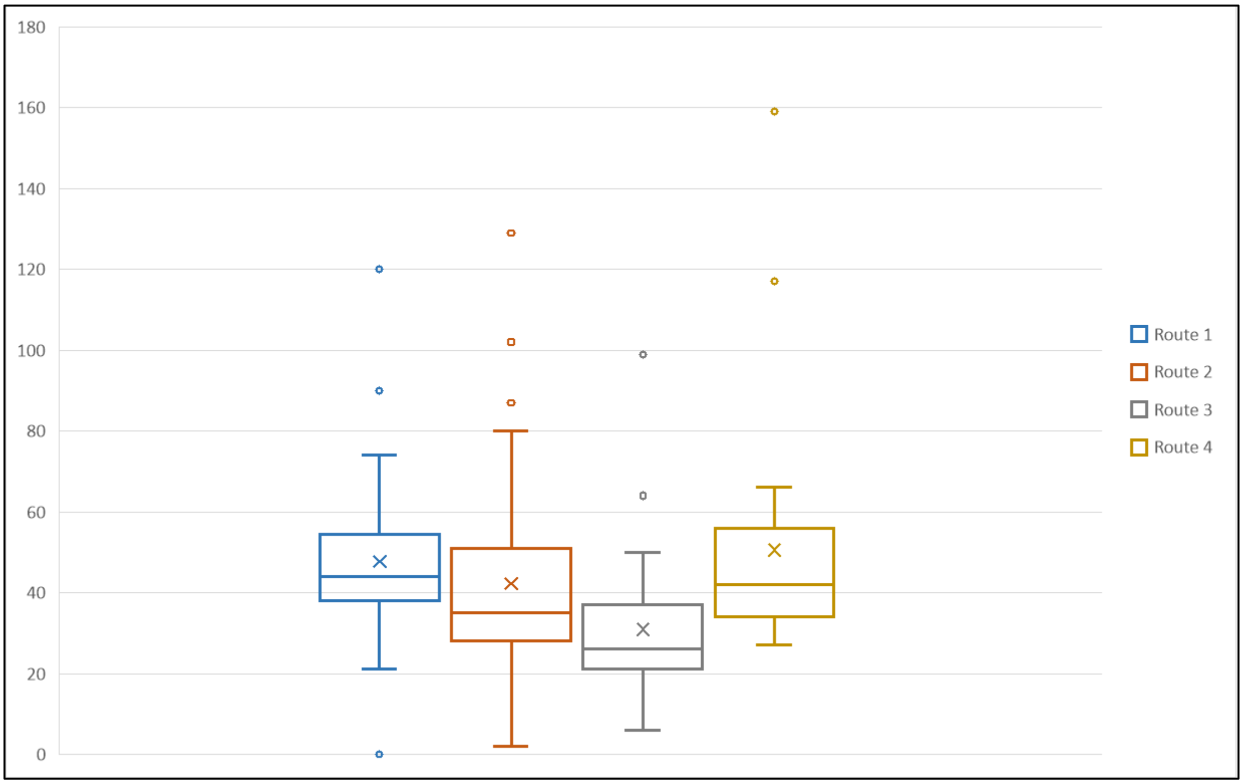


Figure 33: Number of Small Bumps

Table 18: Small Bumps Summary Statistics

Route ID	Count	Minimum	Median	Average	Maximum
1	29	0	44	48	120
2	35	2	35	42	129
3	31	6	26	31	99
4	28	27	42	51	159

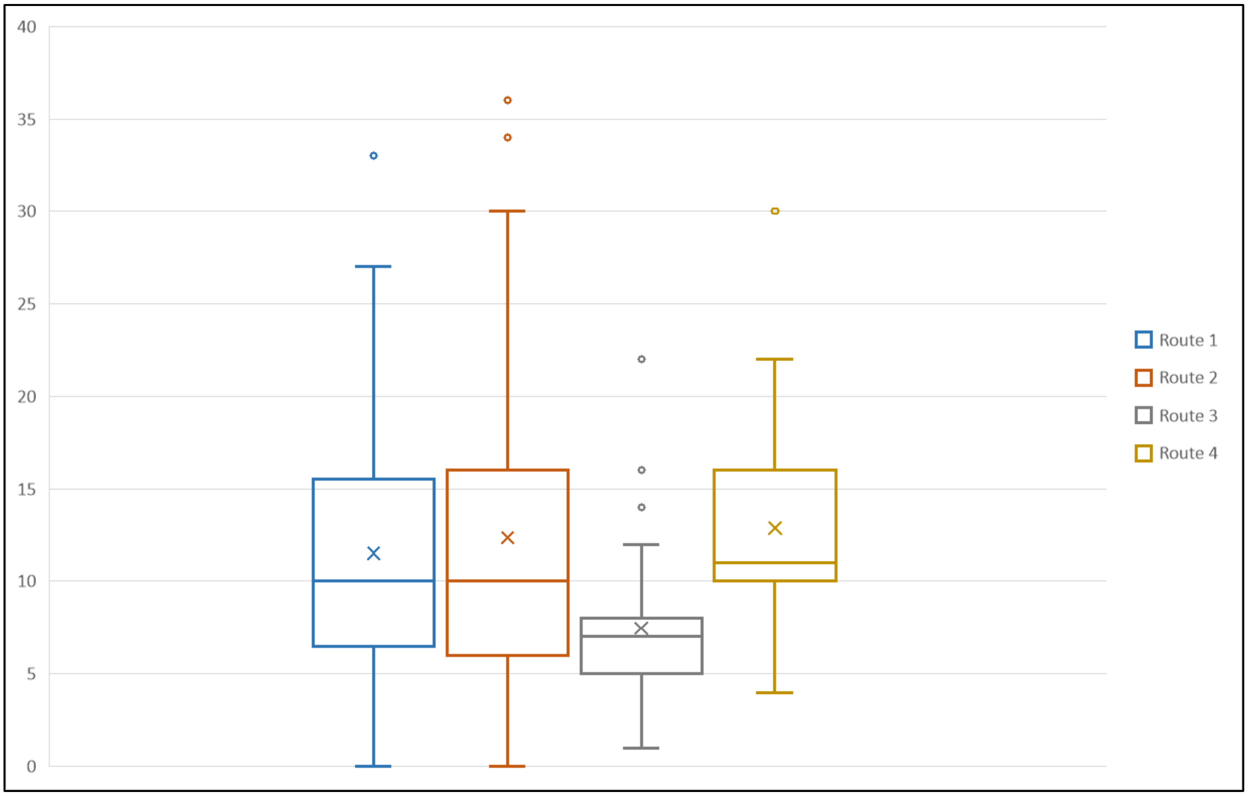


Figure 34: Number of Large Bumps

Table 19: Large Bumps Summary Statistics

Route ID	Count	Minimum	Median	Average	Maximum
1	29	0	10	12	33
2	35	0	10	12	36
3	31	1	7	7	22
4	28	4	11	13	30

The bumps are also categorized into pavement distress events as some distresses, such as alligator cracking, can cause multiple instances of higher or lower amplitudes to occur. This is shown in Figure 35 and summarized in Table 20. Previous studies have found that for motor vehicles, the time that a person experiences and reacts to an event on the road is called the Perception, Identification (understanding), Emotion (decision making) and Volition (execution) time or PIEV time (Iowa Department of Transportation Office of Traffic & Safety, 2013; National Committee on Uniform Traffic Control Devices, 2000). This is the time needed for the operator of a motor vehicle to react to the event and execute decisions to avoid failing to meet the conditions of the event. An example is a sinkhole with signs and barriers surrounding it to inform motorists to avoid falling into the sinkhole. The PIEV time is typically used to determine the location of warning signs and can have a minimum time of 1.6 seconds to a maximum of 10 seconds based on the motorist's speed and the time to execute a decision such as stopping or changing lanes (Hall J. W., 1990; National Committee on Uniform Traffic Control Devices, 2000). The PIEV time is used differently in this thesis as it is used to identify the minimum time that a cyclist feels and reacts to a bump when riding on an ECC. This minimum time is used to determine the minimum number of vibrations data points that result in the series of points to be considered as an event. The 1.6 seconds is measured for a gasoline-powered vehicle that decelerates at a rate of 3.0 m/s^2 for a 30 km/h road. Due to the electric motor of the ECC, the bike can decelerate at the same or faster rate as a gasoline vehicle, the minimum PIEV time can be used. ECCs have fewer dampening measures to reduce the strength of vibrations felt by cyclists and are limited to a maximum speed of 32 km/h compared to motor vehicles which means that the PIEV time would be low for most ECC users. The datapoints for the gyroscope are recorded every 0.5 seconds. As a result, for a bump to be considered an event, there must be at least three or more data points that register amplitudes that alternate between less than 0.8 and greater than 1.2 or the reverse. Events where the amplitude is higher than 1.2 or less than 0.8 for three or more data points are also considered because some of these distresses occur in areas where the participant would have slowed down and stopped near or on the distress, which would cause the acceleration or deacceleration to fluctuate beyond the typical vibration range. The results show that participants on route 4 experienced the most significant number of pavement distress events, with an average of 5, whereas participants on route 3 experienced the least number of pavement distress events, with an average of 2. This translates to the maximum number of events experienced on each route. Route 4 had a few sections where the events repeatedly occurred at the locations listed in Table A2 in Appendix A. It is seen that a few participants, particularly those who experienced a high number of larger and smaller bumps, also had a large number of events significantly greater than the average.

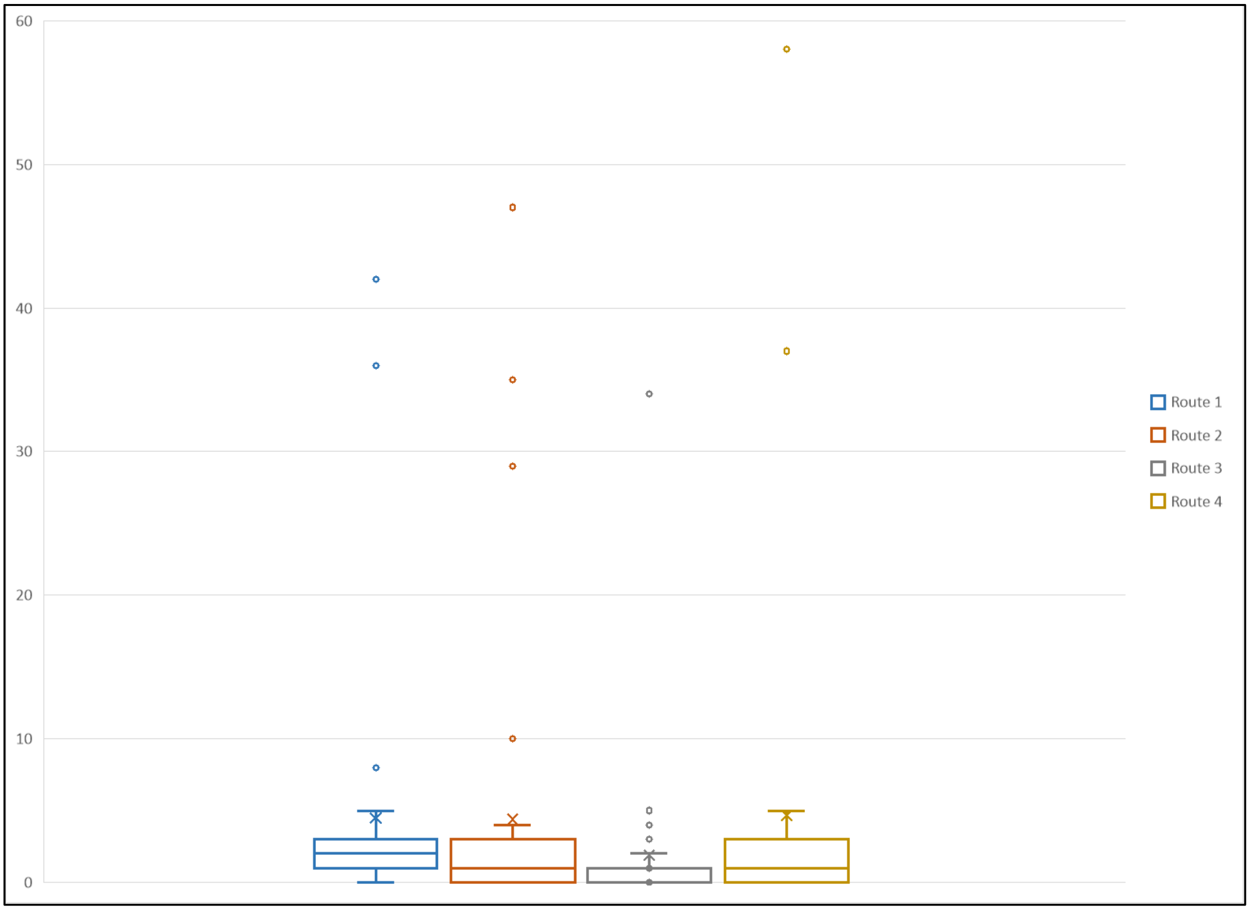


Figure 35: Number of Pavement Distress Events

Table 20: Pavement Distress Events Summary Statistics

Route ID	Count	Minimum	Median	Average	Maximum
1	29	0	2	4	42
2	35	0	1	4	47
3	31	0	2	2	34
4	28	0	1	5	58

The method used to determine the quality of the pavement by grouping repetitive large bumps into pavement events allows us to know how many cracks, ruts and depressions the route has. This is similar to how the remaining functional period (RFP) previously discussed in the literature review is determined. For the RFP, the vehicle has to ride over the pavement distress and complete a ride quality survey afterwards. However, the ride quality survey is subjective, and the RFP uses may vary among different people as a result. The use of a gyroscope to collect data on the ride quality is objective and would lead to more consistent results when the ECC goes over the distress identically each time. The method used relies solely on the vibrations and cannot identify the exact type of distress without visual instruments such as a video camera. Purely visual distress such as pavement bleeding would not be registered by the gyroscope. The gyroscope by itself is limited in its ability to determine the RFP, but when used alongside the ride quality survey assists in verifying ride quality survey results.

5.2.4 Video

The video results consist of the total number of pedestrians passed, the object frequency and the total number of near misses and collisions. A manual count of each participant's ride for each route is performed to estimate the totals. For the pedestrians that the ECC passed, pedestrians are counted if they are near the ECC when they passed the pedestrian either on a pathway or on an adjacent sidewalk closest to the ECC, regardless of whether they are standing or moving. For the vehicles that passed the ECC, only moving vehicles were counted, which included all vehicles moving in the same or opposite direction as the ECC. The vehicles included cars, trucks, and buses, as well as bicycles, motorbikes, and micromobility vehicles. This also included equipment used by the university to maintain the grounds, such as golf carts and farming machinery.

The collisions recorded are actual collisions that are caught on camera or are reported by the participant or the study facilitator with one or more vehicles, cyclists, pedestrians, or property and involve the participant or study facilitator themselves. Near Misses consisted of the participants self-reporting of near misses they felt they had. These are checked with a video of their ride within the reported area to confirm their report. Also, near misses are manually counted for each participant for each route, with self-reported segments not counted to avoid double counting. These near misses included any vehicle or pedestrian within 1 m or less of the ECC.

Figure 36 and Table 21 show the pedestrians passed for each route. For the number of passing vehicles and pedestrians, a higher value indicates a poorer-performing route. Route 3 had the most significant average number of pedestrians at 15 due to its proximity to mixed-use facilities, including a shopping centre, food court, library and various educational facilities for most of the route. Route 4 and Route 3 have the most significant averages. Similar to Route 3, the route passes through several mixed-use facilities, including a subway station and several bus stops. Route 1 had the lowest average number of pedestrians at 11 due to its use of routes that have segments where there is little to no built-up development nearby. Route 4 had a higher median than Route 3 due to its mixed-use areas, including residential buildings, which Route 3 lacked. Route 3 had more educational facilities, which have an incoming and outgoing number of pedestrians at certain times of day, causing the number of pedestrians seen to vary consistently.

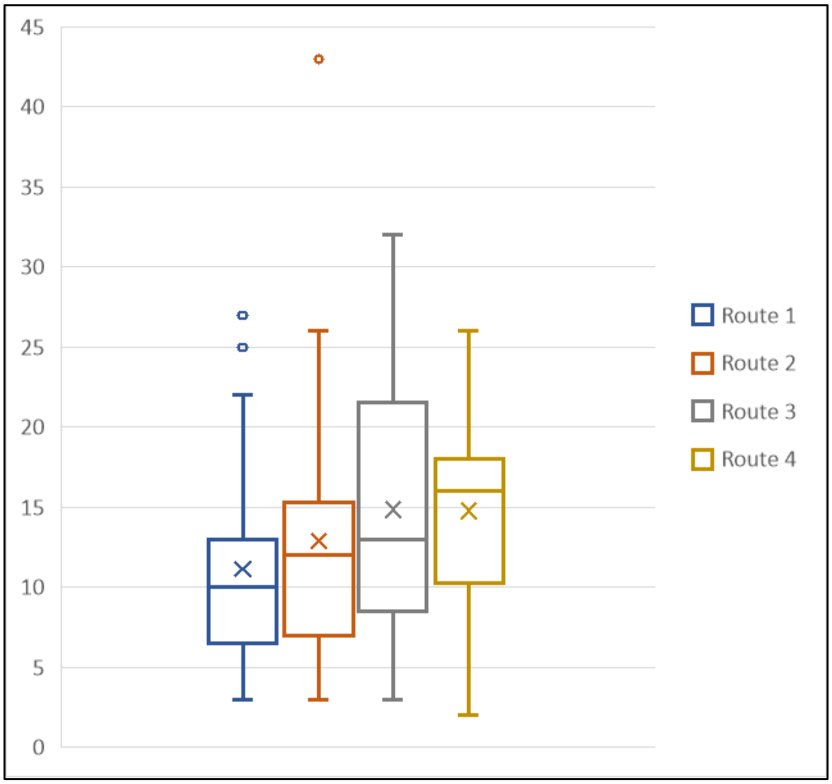


Figure 36: Pedestrians Passed

Table 21: Pedestrians Passed Summary Statistics

Route ID	Count	Minimum	Median	Average	Maximum
1	367	3	10	11	27
2	490	3	12	13	43
3	549	3	13	15	32
4	472	2	16	15	26

The number of vehicles that passed the ECC is shown in Figure 37 and Table 22. Route 4 had the most significant average number of cars at 16 due to its use of high-traffic volume roadways along the route. The mixed-use facilities along the route mean that vehicle traffic is higher than on route one, which also uses a high-volume roadway but is less developed. Routes 2 and 3 had the lowest average number of passing vehicles at four each due to their use of multi-use pathways that are required to reach several nearby facilities and that do not have any nearby through roads.

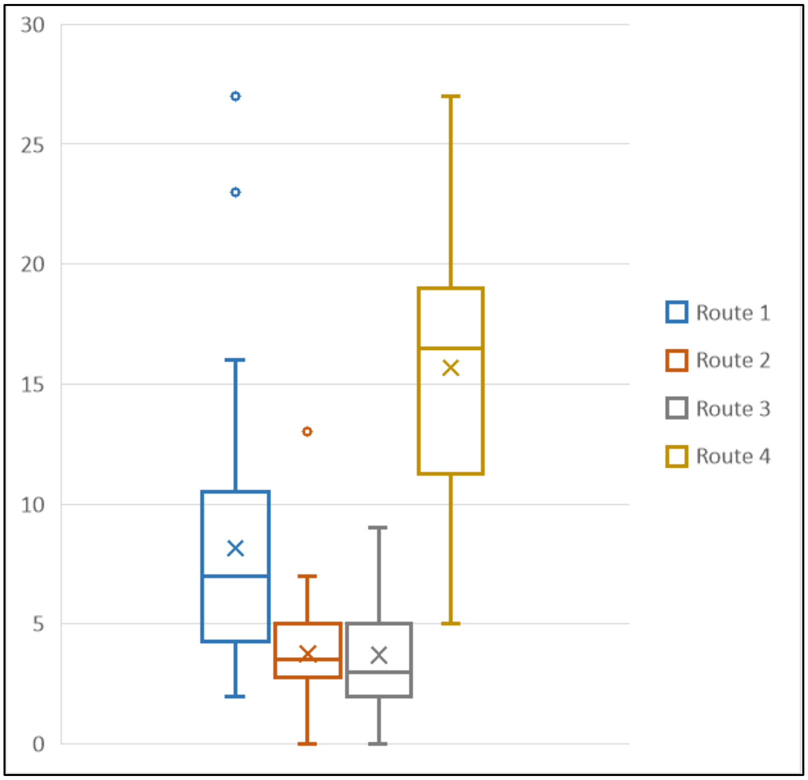


Figure 37: Passing Vehicles

Table 22: Passing Vehicles Summary Statistics

Route ID	Count	Minimum	Median	Average	Maximum
1	261	2	7	8	27
2	143	0	4	4	13
3	141	0	3	4	9
4	502	5	17	16	27

The total number of near misses and collisions is shown in Figure 38. Since the study is completed in 4 weeks, the number of collisions and near misses experienced is expected to be low. For the number of collisions and the number of near misses, a higher value indicates a poorer-performing route. Table 23 lists the collision that occurred. A total of 6 collisions occurred with all of them self-reported: 2 minor injury collisions, 2 visible property damage collisions and 2 non-visible property damage collisions occurred. No additional collisions are seen from the Go Pro video data. Routes 2 and 4 have the most significant number of near misses at eight each, with route two also having the most substantial number of collisions at three consisting of 2 property damage-only type collisions and one injury type collision. Route 3 is slightly lower at seven near misses and two collisions. All three routes had a high amount of vehicle or pedestrian traffic and travelled through areas with mixed-use facilities, which increased the possibility of experiencing a near miss or a collision. Route 1 used a large portion of unmarked roads but has the least number of visible near misses at 2, and 0 collisions are seen or experienced. The visibility and wider lanes along the route may have contributed to its lower numbers compared to the other routes. It should be noted that due to the low sample size of collisions and near misses due to the short study period and lower-than-expected vehicle and pedestrian traffic volume during the period, the route's overall safety may not be fully reflective of this result.

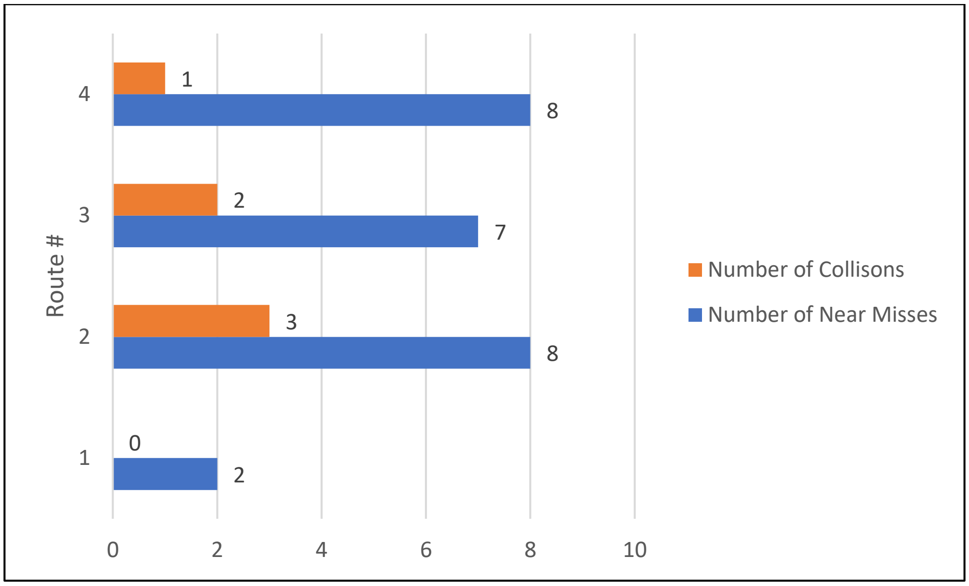


Figure 38: Collision Risk Per Route

Table 23: Collision Details

Route ID	Collision Details	Type of Collision	Cause
2	Sharp Right Turn at high speed	No Damage	Speed
2	Fell off ECC while swerving to get back on the path	Injury, Property Damage	Speed
2	Wide Turn that tilted the ECC to one side	No Damage	Turning
3	Bumped into a concrete barrier	No Damage	Turning
3	Rear Ended facilitator's ECC while getting off to cross	No Damage	Speed
4	ECC wheel went over a large pothole causing it to tilt over	Injury, Property Damage	Pavement Condition

Based on the different sections of the survey and the instrument results, route 1 is ranked as the best route but there are contradictions in some of the results. The AHP weights and results from the route choice model in the next section should provide a more precise outcome of essential cycling variables that affect ECCs and the routes most suitable for them. The travel time and distance rankings show that participants ranked route 1 as having a better travel time and distance than route 3 which is the shortest route according to participant's recorded time spent cycling on the route. However, the travel time results from section 5.2.1 show that the average travel time between routes 1 and 3 differed by approximately 20 seconds. The average speed along Route 1 is 3.0 km/h greater than on Route 3. This noticeable increase in speed would have resulted in the route feeling shorter as the participants kept moving more frequently on the route compared to route 1. Route 3 has more junctions and pedestrian traffic which would require participants to reduce their speed, resulting in the route being perceived as longer. Route 1 has significantly fewer junctions and pedestrian traffic which would result in fewer moments where participants would have to reduce their speed. This results in them perceiving Route 1 as the shortest travel time route compared to Route 3. The 0-10 ratings of the routes in the travel time and travel distance categories from section 5.1 also showed that routes 1 and 3 had very close average rankings. As a result, the perception of the travel time and travel distance did affect the participant's route rankings for the two categories due to an increase in the average speed of participants travelling on route 1.

Chapter Six: Model Results

6.1 AHP Weights

The section discusses the outcome of the AHP weights for each route variable. It should be noted that one participant's data is not used for the remaining analysis due to the data being severely incomplete. Figure 39 shows the AHP weights computed from the aggregated AHP results, while Table A3 in Appendix A shows the aggregated response matrix. The consistency ratio for the aggregated AHP weights is 0.0252, below the upper recommended consistency ratio of 0.1. This indicates that the results, when aggregated, are consistent. Some of the participant's matrices had consistency ratios significantly greater than 0.1, with a few beyond the 0 to 1 range, which indicates that these results are not consistent at all. This is due to several variables. First, for larger matrices, it becomes more challenging to reach a consistency ratio of 0.1 due to the large number of variables and combinations that have to be considered (Nolberto, 2017). A study by Sakhardande et al. (2022) found that as the matrix has more than 6 to 7 criteria, it becomes more challenging to reach a consistency ratio of 0.1.

The AHP results had participants consider 11 criteria in 55 sets of pairwise comparisons. The larger number of criteria may be affected by the participant's interpretation of the variables, which may cause inconsistencies to arise. This leads to the second variable, which is the human nature of this data collection procedure. Since the study revolves around a mode of transport that is uncommon in North America, many people, including the target demographic for this mode, are cyclists not having enough knowledge about the mode as well as the different types of variables that they would have experienced on the route. The participant sample also does not have a single ECC courier who would be more experienced in using these bikes in a work-related scenario compared to conventional cyclists and enthusiasts. There is little past research relating to the development of a project of this type, so some methods derived from conventional bike research may not be as effective for ECC research. Some participants are not positively participating in the study, which could have resulted in responses that are highly inconsistent with each other. The results show that participants weighted the risk of collision as the most important, with a percentage of 25.5%, followed by visibility at 13.0% and pavement at 9.9%.

The consistency ratios are sorted from least to greatest and then plotted to see where the consistency trend starts to deviate significantly. Two scenarios are created: Scenario 2, which computed the aggregated AHP weights only considering participants with consistency ratios of less than 0.91, and Scenario 3, considering consistency ratios of less than 0.5. Scenario 1 refers to the "all responses" case. These are two sections where the consistency ratio trend deviates significantly. This would remove the poor responses and see how the AHP weights change without them. Figure 39 visualizes the AHP weights for each respective scenario. Table A4 and Table A5 in Appendix A show their respective aggregated response matrix. The consistency ratios for Scenarios 2 and 3 are 0.0231 and 0.0202, respectively. The removal of more inconsistent results led to a more consistent set of AHP weights, which is to be expected. This did not significantly change the consistency ratio from the full response matrix, but the order of the AHP weights shifted slightly in Scenario two and even less in Scenario 3. The results for Scenario 2 show that variables such as pavement and infrastructure saw small changes in their weights, but other variables did not significantly change. The situation is identical to Scenario 3, which saw minor changes to the AHP weights, with the order of the AHP weights being identical to Scenario 1. As a result, due to its lower consistency and similar values to Scenario 1, Scenario 3 is used for its final AHP weights. This means that the risk of collision is the most important variable among the participants, followed by visibility, pavement and object frequency.

Two additional scenarios are created based on the grouping of participants into two categories as previously discussed: Enthusiast cyclists, labelled as Scenario 4, and Leisure cyclists, labelled as Scenario 5. For these scenarios, the average speed categories across all of the routes the participant completed are used to divide the participant pool into two categories. The trends between the participants are looked at to see if there is a clear divide between enthusiasts and leisure cyclists. Most of the trends are directly determined from the results, with a few, mainly those related to discomfort, derived from the results. Table A8 and Table A9 in Appendix A show the breakdown and overall trend of the two participant categories. Participants separated into the enthusiast class are more physically fit, cycled more regularly (3-4+ days), cycled in wet and temperate weather conditions, had a lower number of safety events and tended to rate their enjoyment to be higher, but their discomfort to be higher due to the faster speeds requiring higher acceleration rates which amplifies discomfort over poor pavement. Inversely, the leisure class is less physically fit, cycled less often in less adverse weather, and is more comfortable due to cycling slower, with distresses being detected less frequently. It should be noted that 77% of enthusiast cyclists had a route attractiveness rating greater than 7.0 whereas 28% of leisure cyclists had a route attractiveness rating greater than 7.0. This means that enthusiast cyclists more often gave higher ratings for the routes compared to leisure cyclists.

Separating the participant pool into these two groups revealed that both groups of cyclists had higher consistency ratios, resulting in relatively less consistent results but still below the 0.1 recommendation. Scenario 4 had a consistency ratio of 0.049, while Scenario 5 had a consistency ratio of 0.033. The AHP weight breakdown also slightly changed compared to Scenario 1. For Scenario 4, the risk of collision and visibility AHP weights decreased while the sightlines, travel time and pavement AHP weights increased. For Scenario 5, the risk of collision, visibility, travel time and distance decreased while pavement increased, and discomfort decreased. This makes sense since these AHP weights are based on more casual cyclists who tended to cycle slower and more leisurely compared to Scenario 4, where sightlines and travel time are more important when cycling at faster speeds for more essential purposes.

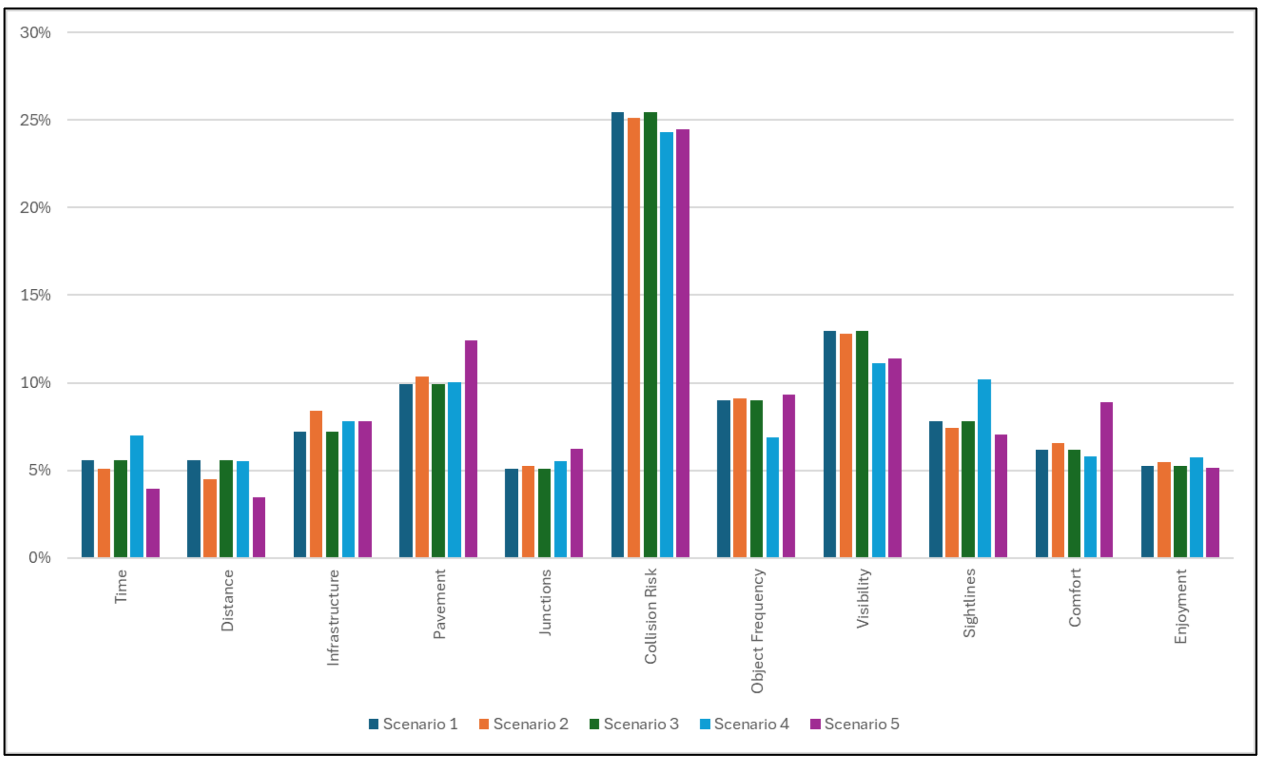


Figure 39: AHP Weights

Table 24: Consistency Ratios

Scenario	**1**	**2**	**3**	**4**	**5**
Consistency Ratio	0.0252	0.0231	0.0202	0.0490	0.0330

The AHP weights in Scenario 2 are used for the ECC score due to the low consistency ratio while incorporating the majority of the participant's AHP data, resulting in AHP weights that have sufficient data to accurately describe the participant's priorities. Scenario 3 only incorporated half of the data pool compared to Scenario 2's 34, which is slightly lower than Scenario 1's 40 scenarios but removes the most inconsistent individual results from the dataset.

Comparing the order of the variables based on their weightings to other indices from the literature review, Van Dyck et al., (2012) bikeability index which outputted results in terms of probabilities found that safety is the most important with a probability of 60.3%, enjoyment (referred to aesthetics in Van Dyck (2012)) at 45.4% and cycling infrastructure at 13.0%. These probabilities are higher than their equivalent AHP weight categories. Safety is weighted significantly more than the other variables in addition to being the most important variable seen in the two models. There is a larger gap between the enjoyment weightings, however, this may be attributed more to the location of the routes and the choice of study area such as having the routes pass through upkeep complete streets compared to minimally maintained residential roads. The difference in the safety weightings could be due to the study area and the routes used as the study is preformed on low-traffic volume routes compared to the higher traffic volume routes used in Van Dyck's study. This could also be due to the participants not being familiar with ECCs compared to conventional bicycles so their enjoyment levels may not have as been as high as a cyclist that regularly used an ECC.

Arellana et al., (2020) bikeability index looked at the most important variables for two categories of cyclists – frequent and infrequent cyclists. We can compare these results with Scenarios 4 and 5 respectively which are set up in similar categories. Their model found that for frequent cyclists that commute to work, pavement condition is weighted the most at 35.7% followed by safety at 34.3% and visibility of the cyclist at 25.2%. For infrequent cyclists commuting to work, these weightings are the same as the frequent cyclists for the top three weightings but differ for the rest of the weightings. Scenario 4 had safety, visibility and sightlines as the top three while Scenario 5 had safety, pavement and visibility as the top three weights. Scenario 4 is less similar since it did not have pavement condition in the top three while also weighing safety more and visibility less than in the frequent cyclist's category. Scenario 5 is similar to the infrequent cyclist's category in terms of the order of the weightings, but safety is weighted more in Scenario 5 while pavement and visibility are weighted less. These differences are not as large compared to Van Dyck's index and could be attributed to the focus on cyclists who commute to work compared to our use of cyclists who either cycled to commute, for sports shopping or leisure purposes. The division of cyclists considering their cycling frequency yields similar patterns to how the cyclists are categorized based on their experience and ride performance for the AHP weights. This shows that categorizing cyclists into different groups results in changes in the variables prioritized and is useful to target a certain type of cyclist to make routes more attractive for them to use. Different classes of cyclists are required to prioritize variables differently. For municipalities which have a wide range of cyclists that use the routes in the jurisdiction, it can be challenging to decide what variables of the routes are to be addressed within time and budget. The use of weights to prioritize a cyclist's route preferences as well as developing weights for different categories can identify if there are any patterns between the priorities such as safety appearing in the top three weights of different cyclist types. This allows decision-makers to be able to implement measures that can make the routes more attractive for all cyclists while lowering the barrier to entry by using active transportation in people's lifestyles.

6.2 Ordered Logit

The logit model is built upwards, where the variables that correlate the most with the independent variable are added first, with the lowest correlation variables added last. This allows for a model that minimizes issues with variable correlations. For two variables that are highly correlated with each other, the most impactful out of the two is kept in the model. For example, if travel time and travel distance have a high correlation with each other, one of those variables would be removed from the input data for the model.

The inputs for the ordered logit model are analyzed by computing the Spearman rank correlation for each input. This is performed to identify which variables from the 0-10 ratings and the instrument data are highly correlated with other variables and how much they influence the route choice model results. To identify which correlation technique to use, the weighted average of the AHP pairwise values is plotted. The weighted average is computed for each variable within the pairwise comparison and is sorted from least to greatest. Importance values that correspond to the variable listed second in the pair are converted to negative values while the value that corresponds to the variable listed first in the pair remains positive. The points represent which variable was chosen as the more important among the pairwise comparisons with the magnitude indicating its relative importance among the pair. This is seen in Figure A12 in Appendix A, where the relationship between variables and their importance value is nonlinear (Spearman, 1904). As a result, the Spearman rank correlation is chosen due to its ability to assess the relationship between the variables when the relationship is nonlinear.

It is found that variables such as the number of big pavement bumps and small pavement bumps, as well as the road, sharrow, and multi-use path percentages, had high correlations compared to the other inputs which would influence the results toward them. The pavement bumps are highly correlated with each other as well as for the cycling infrastructure percentage. As a result, some of the inputs for the route choice model are combined to match the categories of the AHP weights. This includes integrating the road, sharrow and path percentage as infrastructure, using events instead of bumps for pavement as they are derived from the same data and taking separate inputs such as near misses and collisions or number of vehicles and pedestrians and summing them as one input. It is found that these combined inputs still had higher correlations with other variables such as infrastructure percentage having a correlation of -0.71 with travel distance.

A scenario that removed correlations of variables greater than 0.6 is looked at to further identify correlations between variables without the influence of the higher correlation variables. Device Output variables with strong relationships with the dependant variable are the number of junctions, the percentage of cycling infrastructure and the object frequency. The variables obtained from the device output are strong due to how simple they are to measure mostly being a count or a linear measurement. From the Route & Variable ratings, the variables with relatively strong correlations include the comfort rating, enjoyment rating, safety rating, pavement condition rating and visibility rating. These Route & Variable ratings are strong due to the variables not being dependent on the effect that a set of short-distance routes would have on a participant's rating. It is found that lower ratings are associated with higher discomfort, higher travel time, a higher number of pavement events, a higher number of safety events and a higher object frequency. The higher discomfort relationship is less consistent than the other relationships. Other relationships found from the Route

& Variable ratings are that lower ratings are associated with lower travel time ratings, higher discomfort ratings, lower enjoyment ratings, lower safety ratings and lower pavement ratings.

However, these relationships between the explanatory variables and the dependant variable are not as strong as expected with rank correlations below ±0.6 for the inputs whereas a strong relationship would correlate closer to ±1. These lower correlations could be due to participants not considering the relationships of the variables when answering the rating questions as well as being less critical of their responses which can result in responses that have a weaker relationship between multiple variables. It could also be due to how the variables are collected during the study such as the pavement events derived from the gyroscope data collected did not impact comfort as much compared to the comfort ratings which rated most of the routes as moderately comfortable or around 5 out of 10 despite the high number of pavement events recorded. In the case of comfort, the vibrations experienced on the handlebars where the device is located may have been different compared to the vibrations from the seat. The vibrations could have been dampened from the seat as it is positioned further back from the front of the ECC compared to the handlebars which experience vibrations travelling from the front trunk more than the seat does due to solely being fastened to the trunk body.

The inputs for the model are modified based on the Spearman correlations as seen in Table A10 in Appendix A. The observed travel time, travel distance and average speed variables have a relatively high correlation with each other around ±0.55. Since the travel distance for each of the four routes is a fixed distance, the travel distance is removed as an input for the model. The infrastructure, being a combination of the three cycling infrastructure percentages, is also fixed for each route, with deviations off-route not amounting to noticeable differences. This would also be omitted from the model.

The results from Model 1 and Model 2 are shown in Table 25, based on measured data collected from the participant rides. Model 1 shows only the discomfort variable with a statistically significant parameter above 90% with a negative relationship to the overall route rating. This indicates that a trip exhibiting higher discomfort, as measured by the gyroscope, results in a worse experience for the rider. However, the lack of statistical significance among any other parameters suggests that the model itself is not a good fit for the data. Model 2 is therefore estimated using backward stepwise elimination to remove the least significant parameters. This results in two variables remaining in the final result, including object frequency and a Route 4 dummy variable. The object frequency has a negative statistically significant parameter above 90%, while the Route 4 variable has a positive statistically significant parameter above 95%. It should be noted that the Route 4 variable was added to the models after all other variables had been tested since it appeared that the attractiveness of Route 4 was not appropriately captured by prior model iterations which led to the initial model 1 and 2 results being counterintuitive. The overall lack of statistical significance suggests that the measured variables did not properly align with the experience or perception of the users, therefore the subjective ratings are tested in the next models. The AHP weights assign a weight of 8% - 9% for object frequency depending on the scenario, lower than half of the other variables weighted.

Table 25: Ordered Logit Models Based on Measured Variables

	Model 1		**Model 2**	
Variable	**Parameter**	**t-statistic**	**Parameter**	**t-statistic**
Discomfort	-0.004	-1.71*		
Travel Time	0.113	0.41		
Average Speed	0.158	0.51		
Pavement Events	-0.069	-1.20		
Safety Events	0.408	0.84		
Intersections	0.012	0.03		
Turns	-0.001	0.00		
Object Frequency	-0.047	-1.17	-0.066	-1.86*
Route 4	1.795	0.75	1.745	2.57**
Thresholds				
0	0.000	N/A	0.000	N/A
1	0.281	1.01	0.227	1.01
2	0.521	1.44	0.427	1.44
3	1.472	2.76***	1.174	2.76***
4	1.775	3.15***	1.407	3.13***
5	2.667	4.29***	2.147	4.31***
6	3.624	5.44***	2.94	5.54***
7	5.063	6.99***	4.339	7.31***
8	6.625	8.38***	5.833	8.74***
9	8.016	9.35***	7.121	9.69***
McFadden Pseudo R^2	0.239		0.270	
Number of Observations	110		110	

**** 99% statistical significance, ** 95% statistical significance, * 90% statistical significance*

The results from the Model 3 are based on the ratings provided by participants. Table 27 shows that the variables that are the most statistically significant from the survey ratings are the safety rating with the highest statistical significance, followed by the enjoyment rating, the Route 4 dummy variable, and the visibility rating. These four variables all exhibit a positive relationship with the overall attractiveness rating of the routes. The safety rating and visibility rating are also two of the top three most weighted variables from the AHP weights. Enjoyment has a low weight in the AHP weights which is inconsistent with the ordered logit model result. While the correlation with enjoyment is correct to what participants experienced, compared to the 10 other variables, enjoyment is of less importance. Model 4 presents the results of a backward pairwise elimination process to remove parameters that exhibit low statistical significance. This results in the same four variables as previously mentioned, but the order changes slightly when ranking these variables by statistical significance. The enjoyment rating appears as the most statistically significant parameter in Model 4, followed by the visibility rating, the safety rating, and the Route 4 dummy variable. Overall, safety and visibility are rated more important from the ordered logit model and the AHP weights.

Table 26: Ordered Logit Model Based on Participant Ratings

	Model 3		**Model 4**	
Variable	**Parameter**	**t-statistic**	**Parameter**	**t-statistic**
Travel Time Rating	-0.025	-0.19		
Travel Distance Rating	0.014	0.10		
Comfort Rating	0.179	1.23		
Enjoyment Rating	0.423	2.51**	0.587	4.10***
Safety Rating	0.411	2.68***	0.383	2.56**
Pavement Rating	0.149	1.00		
Visibility Rating	0.355	2.14**	0.458	3.02***
Route 4	1.442	2.39**	1.155	2.13**
Thresholds				
0	0.000	N/A	0.000	N/A
1	0.327	1.02	0.327	1.02
2	0.635	1.48	0.626	1.47
3	1.749	2.92***	1.700	2.90***
4	2.104	3.36***	2.034	3.34***
5	3.294	4.72***	3.182	4.71***
6	4.546	6.01***	4.407	6.04***
7	6.762	7.48***	6.552	7.53***
8	8.834	8.68***	8.561	8.74***
9	10.523	9.50***	10.260	9.51***
McFadden Pseudo R^2	0.411		0.403	
Number of Observations	110		110	

**** 99% statistical significance, ** 95% statistical significance, * 90% statistical significance*

6.3 The ECC Score

One of the goals of developing the ECC score is to provide a methodology that can be replicated by last-mile delivery companies and other decision-makers to determine the best routes for ECCs within their service area. The 3-axis gyroscope used to collect the pavement and comfort data is one of many that can be used. However, the placement of the gyroscope on the ECC can affect the magnitude of the vibrations recorded by the instrument (ex., Placing it in the middle of the frame can yield different vibrations than closer to the handlebars vs. placing it directly under the cyclist). The ECC used in the study had no way to mount the gyroscope on the middle frame rigidly without causing false readings from the movement of flexible-type mounts. Since each participant had a different seat height, placing it under the seat would not yield results that can be compared or combined due to the position of the instrument constantly changing between sessions. Also, due to the way how the human body experiences and interprets vibrations, the discomfort experienced may differ between people. As a result, a simplified ECC score that omits the gyroscope is created to ensure that the scoring methodology can be replicated more easily. In addition, data that is only collected subjectively with no objective counterpart collected, such as enjoyment, is also removed as the participant's ratings vary depending on the makeup of the participant pool. The variables that are removed are visibility, collision risk, sightlines, comfort and enjoyment. It should be noted that the collision risk and sightlines can be determined from objective data, but the collision risk requires a larger dataset than the one recorded to calculate for each intersection along the route.

Figure 40 shows the AHP weights for the simplified ECC score using Scenario 2's dataset. The consistency ratio for the simplified version is 0.023, similar to that of Scenario 2. Since some of the variables are removed, the AHP weights have increased. The object frequency accounts for 33.5% of the AHP weights, which is the most significant change from the full ECC score. Both the time and distance were kept in the simplified ECC score despite their known relationship to each other because their correlations between each other were not that high with a correlation of 0.42 as seen in Table A10 in Appendix A. Comfort is correlated higher with time than distance is with a value of 0.50. Unlike a motor vehicle, the travel distance when cycling is influenced by additional factors such as the amount of physical effort needed to propel the bike and is not solely correlated with the travel time and speed.

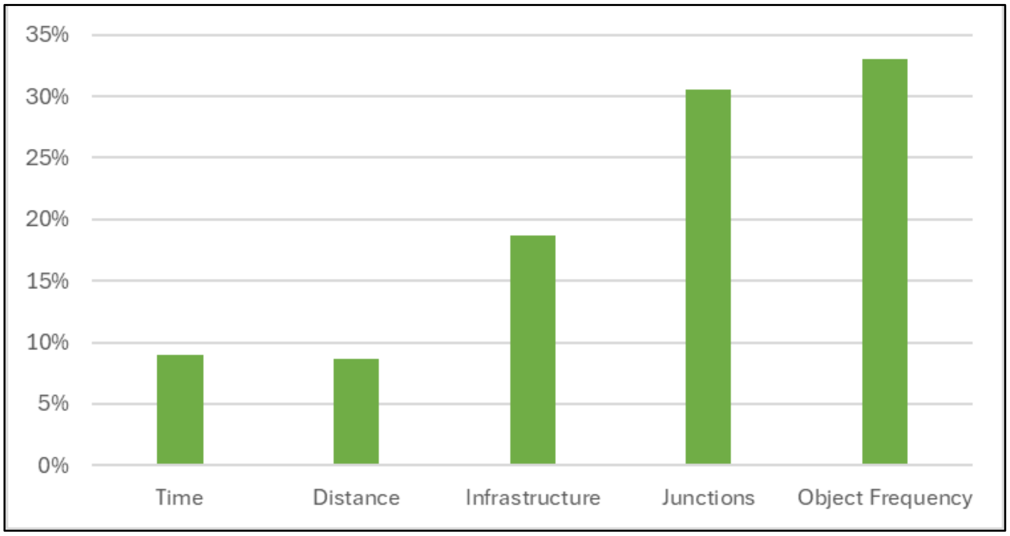


Figure 40: AHP Weights For the Simplified ECC Score

The ECC score for all four routes is shown in Table 27 along with the route attractiveness ratings from the survey and the ECC score using the full matrix for Scenario 2. The simplified ECC score ranks Route 3 as the best route, followed by Route 2, Route 1 and Route 4. This is identical to the full ECC score, which ranks in the same order as the simplified score, albeit at slightly higher rating values for Routes 1, 2 and 3 and lower for Route 4. Comparing the score to the route attractiveness of each route rated by the participants, the order is reversed compared to the ECC score, where Route 4 is ranked first, followed by Route 1, Route 3 and Route 2. Computing the ECC score for Scenario 4 and Scenario 5 both have the same route order and similar values as the score for Scenario 2. The small participant pool combined with the presence of sampling bias in the route attractiveness rating may have affected the order of the routes. For Route 4, 35% of participants scored the route a 10 out of 10 compared to 19% on Route 1, 16% on Route 2 and 10% on Route 3. The large proportion of significantly higher ratings combined with the small sample size may have resulted in the route attractiveness rating experiencing noticeable sampling bias thus resulting in a high average rating. It is found that Route 4 had the lowest rating in 6 of the 11 variables in the full score including the lowest safety rating which contributed to its low ECC score. The same ratings should have resulted in the participant scoring Route 4 overall as a less attractive route. A larger participant pool would be less affected by this set of extremely high ratings as sampling bias is less noticeable with larger sample sizes (Vasileiou, Barnett, Thorpe, & Young, 2018).

Since the route attractiveness rating is a broad rating of the route not tied to a specific variable, there may be other variables that were not explicitly mentioned in the survey that may have influenced this rating. One such variable that was measured quantitatively but not through the survey was speed. This difference in order can be attributed to the participant pool's preference to cycle at higher speeds on routes with lower traffic volumes. The overall route attractiveness rating needs to be more specific in what the term overall is defined as to participants such as defining it as a cumulative rating of the individual variable ratings to prevent participants from interpreting the variable to include variables not rated or that are not considered for the score.

In addition, the participant pool does not contain experienced courier cyclists who would be more likely to have experienced an incident from cycling in mixed traffic, resulting in them avoiding routes with high vehicle interaction, such as Route 4, due to issues such as dooring and vehicles and pedestrians not noticing them. Route 2, being the best route for ECCs based on the order of the AHP weights, makes sense since it has the highest safety rating while also having the lowest combined vehicle and pedestrian interaction. One drawback of this route from a logistics perspective is that there is a lower number of nearby commercial establishments where fewer deliveries can be made to and from as it is primarily a residential route with some educational facilities compared to Route 3 or Route 4, with more commercial establishments allowing for more usage as a delivery route.

Table 27: A Comparison of ECC Scores

Route ID	Simplified ECC Score	Full ECC Score	Route Attractiveness Rating from Survey
1	6.6	6.4	7.2
2	7.5	6.8	6.6
3	7.5	7.2	7.0
4	3.4	5.3	7.5

A simple case study is conducted to verify if the simplified ECC score can accurately rate the best route for ECCs in a dense urban environment with a set of different routes. The study area is more extensive and includes various types of cycling infrastructure, such as barrier-separated and non-separated bike lanes and multi-use paths. The data used for this study is obtained from Google Maps, and ratings are determined from a combination of street view images and in-person travel along the routes during the PM peak period. The routes are chosen to have a variety of characteristics that objectively affect the best route for ECCs, such as different types of cycling infrastructure and the number of junctions that would have to be passed. Certain routes that are unrealistically long or pass through too many junctions are not considered, such as routes that utilize 80% cycling infrastructure but are twice the distance and time from the destination. The object frequency is an estimated count of the volume experienced at the time of travelling.

Table A11: Case Study Data in Appendix A shows the data used for the case study. The origin is set to be a major transit station with cycling parking at 1300 Eglinton Avenue West, while the destination is set to be a large bike-accessible outdoor shopping centre at 30 Weston Road. The four routes are visualized in Figure A13-A15 in Appendix A. For the case study, Route 1 is the shortest travel time route, Route 2 is the longest but utilizes the most cycling infrastructure, and Route 3 is similar to Route 1 but with more traffic and fewer turns. Route 4 only uses major roads with minimal cycling infrastructure.

Figure 41 shows the steps for how the input data for a set of routes is computed into weights in an Excel spreadsheet using the simplified model. The example uses the travel time variable, but the process is similar for other variables. Step 1, the travel time for each route is inputted for their respective route ID. In step 2, the AHP weight for the variable is inputted into the adjacent column. The four cells below are used to standardize the variable using the lowest and highest values. These values can be the lowest and highest values from the set of routes or constraints from other related projects. The weights are set so that the lowest weight cannot be negative, and the highest weight cannot be greater than 1.0. Step 3, for variables that use the benefit criterion equation, the values are under the standardized value column whereas the values for variables that use the cost criterion such as travel time are under the corrected value column. Equation 12 shows the formula used to standardize the variable.

$$x_i = y_1 + (x - x_1) * \frac{y_2 - y_1}{x_2 - x_1} \tag{12}$$

Where x_i is the standardized weight, x is the actual value of the variable, x_1 is the lowest value of the variable, x_2 is the highest value of the variable, y_1 is the lowest possible value of the standardized variable and y_2 is the highest possible value of the standardized variable. In step 4, the values are multiplied by the AHP weight to compute the adjusted weight. In step 5, the weights are summed for all of the variables used. In step 6, the weights are multiplied by 10 to express the weighting between 0 to 10. The route with the highest weighting is the most favourable.

Route ID	Time (min)	Weight of Variable	Standardized Value	Correction for Cost Criterion Variables	Adjusted Weight	Sum of Variable Weights	Rating (0 to 10)
	Step 1	Step 2	Step 3		Step 4	Step 5	Step 6
1	25.00	9.00%	0.00	1.00	9.00%	0.69	6.90
2	27.00	9.00%	1.00	0.00	0.00%	0.77	7.69
3	26.00	9.00%	0.50	0.50	4.50%	0.32	3.23
4	25.00	9.00%	0.00	1.00	9.00%	0.42	4.24
Lowest Value	25.00						
Highest Value	27.00						
	Step 2						
Lowest Weight	0.00						
Highest Weight	1.00						

Figure 41: Example of Computing the AHP Weights Using the Case Study

The scores from the case study are shown in Table 28, and it is found that Route 2, with a score of 7.7 out of 10, is the best route, followed by Route 1, with a score of 6.9, Route 4, with a score of 4.2 and Route 3, with a score of 3.2.

Table 28: Case Study ECC Scores

Route	Route Name	ECC Score
1	Shortest Time	6.9
2	Most Cycling Infrastructure	7.7
3	High Traffic Volume	3.2
4	Low Cycling Infrastructure	4.2

The variations are more noticeable due to the lack of a large data sample compared to the field study. This is reasonable as Route 4 uses one of the poorest paved roads in the area, and Route 2 utilizes a multi-use path (Hristova, 2024). Based on the data, the four routes have very similar travel times, resulting in the quality of the route expressed through the variables being a more significant influence. Some of the weights can be adjusted not to weigh certain variables, such as the object junctions too heavily when there is only a marginal difference. This is why route 3 has the lowest score despite being similar to Routes 1 and 2. For this, the minimum and maximum values in the standardization procedure would have to be set to values that the decision-maker can realistically tolerate, such as the minimum object junctions being 2 instead of 25. Route 2 also has the lowest estimated traffic volume. This is similar to Route 2 in the original study area, which utilized a large portion of cycling infrastructure while also using roads with low traffic volumes. Route 4 is also similar to Route 4 in the study area as it utilizes roads with poor pavement for its route.

This case study shows that the score can be applied to a different study area and produce results that are reflective of the route conditions. It demonstrates, from a planning perspective, that this score can be practically used to identify which variables would have to be improved on the s to make them more feasible for ECCs, such as improving the pavement condition or adding cycling infrastructure. It should be noted that specific routes may affect the accuracy of the scores produced, such as routes with abysmal time and distance but with a favourable number of junctions, object frequency and cycling infrastructure due to the AHP weights being standardized from the lowest route value to the highest. One way to account for this is to set realistic boundaries for the weights instead of using the lowest and highest so that the individual weight for each category so that any unrealistic value becomes out of bounds (standardized value is less than 0 or greater than 1) and can be easily identified and removed from the set of routes.

Chapter Seven: Conclusion

7.1 Summary

This research aims to develop a new type of bike score index aimed at electric cargo cycle (ECC) users and courier companies using ECCs as part of their last-mile logistics fleet. A field survey is developed to collect data as inputs for an ECC Score. The survey consists of a questionnaire and a ride along four prescribed routes of different cycling conditions on an ECC. Data is collected for conventional cycling variables and variables that are identified to affect ECCs, such as comfort. Instruments including a Garmin GPS, Strava App, Gyroscope and a GoPro Video Camera are mounted on a three-wheeled ECC used to collect quantitative data. The ECC score is developed by taking the pairwise comparison responses and applying the geometric mean method to determine AHP weights. A route choice model is estimated using an ordered logit.

The survey data is used to categorize participants into leisure and enthusiast cyclist categories based on their demographics and previous experience, ratings of the routes and their cycling performance. The aggregated AHP weights are found to have a consistency ratio below 0.1, indicating that the results are acceptable, according to Saaty (1980). It is found that participants weighted the risk of collision as the most important variable, followed by cyclist visibility to others and the pavement condition of the route. An ordered logit model is developed to identify the most statistically significant variables from the study. The enjoyment rating is the most statistically significant followed by the visibility rating, the safety rating and the comfort. A simplified ECC score is developed to include travel time, travel distance, percentage of cycling infrastructure on the route, number of junctions and the object frequency (number of passing vehicles and pedestrians passed). Based on the simplified ECC score, Route 2 is the best route for ECCs, followed by Routes 1, 3 and 4.

7.2 Limitations

This research identifies three key limitations. First, the participant pool, consisting mostly of students and faculty unfamiliar with electric cargo cycles (ECCs), was categorized into enthusiast-level and leisure-level cyclists based on their cycling habits and performance. Enthusiasts demonstrate higher speeds and better pavement distress avoidance, while leisure cyclists demonstrate lower speeds and comfort. However, the small sample size (45 participants, with data from 39 used) and limited demographic diversity weaken the comparisons. For example, near-miss incidents are rare occurrences with a total of 25 near misses across 110 trips. This highlights the need for a larger and more varied participant base in future studies. The use of a professional/courier participant pool would behave differently from the enthusiast and leisure participant pools because professional cyclists tend to know how to avoid pavement distress as well as to adjust the gears on the bike to reduce physical effort and maximize performance on routes with different conditions. Professional cyclists also ride for longer periods (40-hour average work week) when the effects of travel time and comfort of a route become more noticeable compared to riding the ECC for a couple of hours a week with an enthusiast cyclist. Since couriers perform deliveries during peak travel periods the object frequency (traffic volume) experienced by professional cyclists is high. Safety among other road users and pedestrians is important, especially during these periods when a collision would result in the courier being unable to complete their tour. Overall, it is expected that the travel time, object frequency, comfort and safety will increase.

Another limitation is with regards to the study's route selection and data collection variables impose constraints. Participants cycled four short routes within 40 minutes to avoid survey fatigue, leaving insufficient time for exploring longer or more complex routes. While some participants expressed willingness to tackle more extended rides, the study did not accommodate such options. Additionally, factors such as climate, battery efficiency, cargo capacity, and topography are excluded due to time and environmental constraints. The omission of barrier-separated and painted bike lanes further limited the study's scope, balancing data needs against the risk of participant fatigue. Future surveys could incorporate endurance-based route selection and additional variables to better reflect diverse cycling scenarios. In the simplified score, the time and distance were kept due to their lower correlations compared to other variables which were more highly correlated. An alternative replacement to time and distance in the simplified score is time and slope (topography) which can affect the travel time of an ECC due to the physical effort needed to propel the bike uphill compared to travelling downhill.

In addition, each participant cycled multiple routes once due to the goal of assessing a variety of routes within a limited period. It is found that cyclist familiarity with the route results in better performance. Studies have found that familiarity can result in increased speeds as well as improved trajectories to increase space and time to react to collisions as well as improved navigation of the route (Ranieri, 2016). However, increased familiarity can also lead to inattention and overconfidence on the route which can increase the risk of a conflict or collision to occur (Intini, 2016). Most participants had familiarity with the routes since most of them were students attending the university. However, they are broadly unfamiliar with the operation of ECCs. Therefore, allowing the participants to cycle each route a second time could lead to improvements in their perception of the routes.

7.3 Implications

The research presented in this thesis can be used to influence future policy-related decisions for ECCs. The score can help municipalities understand the variables that cargo cyclists care most about to improve their experience through measures such as dedicated cycling infrastructure, safety enforcement or additional cycling facilities such as bike parking and change facilities. If a street is being chosen as a route for the municipality cycling network but has a high traffic volume and a poor safety experience among existing cyclists, the street would either have to be improved in those categories or identify another option that is adjacent to the original route but considers safety and traffic volume. The ECC score can be transferable to other urban areas where people are using ECCs. As previously seen in the case study, the score can accurately identify the best route for three-wheeled ECCs in an urban area with longer routes, higher traffic count and different types of cycling infrastructure. The separation of participants into cyclist groups can be applied to other studies such that a particular group can be accommodated. For example, if a cycling route is primarily used by enthusiast cyclists than leisure cyclists you would recommend measures to improve the route based on the characteristics of the route that the enthusiast group highly values. The methodology developed for the score can be generalized to develop weights for different ECC configurations and different bicycles. For example, a score for conventional bicycles can be developed that would have different weights than the ECC score.

The route choice model can be used by transportation planners as a tool for future route choice forecasting on routes with the potential for high ECC usage. This can involve looking at streets with a high number of couriers or conventional cyclists and a high number of establishments that tend to cater to the community to identify potential routes, followed by surveying the community on different variables they value when choosing a route to cycle. This can then be used to improve the forecasted routes in terms of variables that the routes may be lacking, such as visibility or pavement. The score can also be used as a tool by last-mile logistics companies to assist in planning ECC tours. The ECC score in the thesis is created using individual trips (i.e. origin to destination) but couriers often perform a tour by chaining multiple trips together. Some trips may take up a large proportion of the tour since each trip represents a single segment. In such cases, a weighted variable can be introduced to match the proportion with a corresponding impact on the ECC score. For example, the average travel time ($\bar{t}_i$) of each trip (i) can be multiplied by its ECC score (ECC_i), sum this term for each trip then divide by the total average travel time for all trips.

$$\frac{\sum_i (\bar{t}_i \; ECC_i)}{\sum_i \bar{t}_i} \tag{13}$$

Future research related to improving the ECC score can be conducted to improve its useability. The ECC design used for data collection—a three-wheeled, moderately sized model—introduced limitations in generalizability. Results may vary with two- or four-wheeled ECCs due to differences in design. Four-wheeled ECCs, offering greater stability and weather protection, likely prioritize variables like pavement condition over comfort, while their larger size complicates maneuverability. Addressing these limitations in future research, through broader participant pools, more varied routes, expanded variables, and diverse ECC designs, would provide deeper insights into ECC usage and infrastructure effectiveness. Two similar scores, one for two-wheeled flatbed style ECCs and another for four-wheeled fully enclosed style ECCs, can be developed to identify the best routes for these bikes and look at how the scores change when using a different type of ECC. A score developed using data primarily from a professional cycling pool can be created using this score as the basis. This allows for a research tool to be developed for last-mile logistics companies or for businesses that have adopted or are interested in adopting ECCs for last-mile logistics. This score can be enhanced using more extensive datasets. This can improve the statistical significance of the variables as participant outliers would be less impactful to the score. The larger datasets could include sociodemographic-related or behavioural experiences that may affect the ECC score and should be looked at compared to the cyclist's overall route selection (gender, neighbourhood safety, low-light visibility, attitude toward ECCs by locals) as well as objective-based variables that are not considered in this score.

The final ECC score results appear inconsistent with the attractiveness ratings provided by survey respondents. The rankings of the route from the attractiveness ratings are in the reverse order as the rankings from the ECC score. For example, Route 4 had the lowest ECC score but was rated the most attractive by participants. Model 1 of the ordered logit do not adequately quantify the benefits for Route 4, as noted by the low statistical significance of most parameters. Model 3 and

Model 4 tell us that respondents highly favoured enjoyment, safety, and visibility, but these are not adequately captured by the quantitative variables. The Route 4 dummy variable is used as a placeholder for the missing information suggesting Route 4 is more desirable. The analysis could be improved if each rating question answered by a respondent is accompanied by a measured quantitative variable and vice versa.

Variables which are broader and less explicit such as the overall route attractiveness should have a clear definition provided to the participant of what "overall" means so that the participant similarly interprets the variable as what the decision maker would expect. This results in the variable becoming a more reliable indicator as it is constrained to a single interpretation. For example, the overall route attractiveness rating should have a similar pattern as the average of the individual variable ratings for each route if the overall attractiveness is defined to participants as only considering the individual variables rated.

ECCs are an emerging mode of transportation in North America, with pilot programs soon having to decide shortly to make ECCs permanently allowed on bike lanes and city streets for businesses and cyclists to use (Ministry of Transportation Ontario, 2021). This research contributes to the topic of ECCs by developing a standardized scoring system that can be used to identify the best route for an ECC based on a set of weighted variables. This work is one of the first scoring systems created specifically for three-wheeled ECCs and their use for performing last-mile deliveries in dense urban areas. This scoring system utilizes the AHP for the creation of the weightings, which are seldom used in cycling research despite being used in transportation planning. The objectives outlined at the start of the thesis have been achieved throughout the project. The different scoring metrics in transportation are reviewed to identify what had to be considered when developing an ECC score, and the field survey can assist participants in assessing the quality and ranking of the four routes based on their experience using the ECC. The field survey allowed the community to learn about ECCs and increase participant's exposure to cargo bikes as an alternative to motor vehicles. The data collected allowed for trends such as between the comfort rating and the pavement condition and to categorize participants based on several patterns. These trends, along with the outputs of the AHP weights and the variable's significance, allowed for the creation of a standardized ECC score that can be used by decision-makers for routes with different variables.

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Appendices

Appendix A: Additional Figures and Results

Elevation Profiles

Figure A1: Route 1 Elevation Profile

Figure A2: Route 2 Elevation Profile

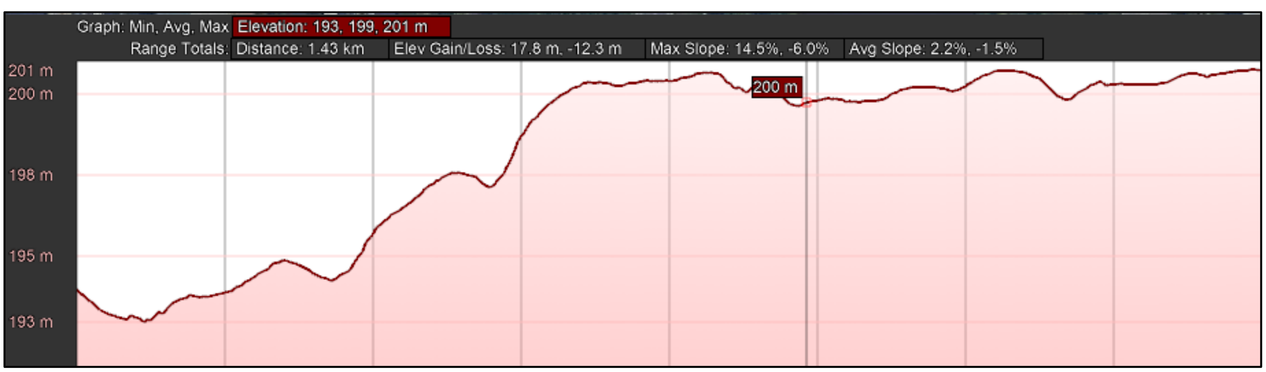

Figure A3: Route 3 Elevation Profile

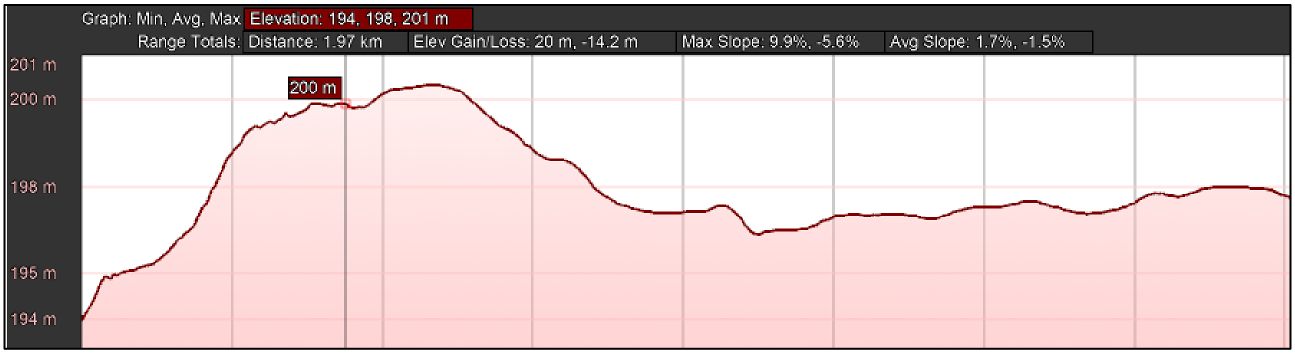

Figure A4: Route 4 Elevation Profile

<u>Route Description</u>

Table A1: Route Directions

Route ID	Route Description (From Bergeron Centre)	Route Description (From 190 Albany Road)
1	1. From the rear of Bergeron, turn left onto Library Lane. 2. Continue straight to Ian Macdonald Boulevard. 3. Turn right along Ian Macdonald Boulevard and continue straight to Chimneystack Road. 4. Turn left onto Chimneystack Road. 5. Turn left at Albany Road and continue straight. 6. Turn left into the 190 Albany Road Parking Lot.	1. Turn right onto Albany Road and follow the road. 2. Turn right onto Chimneystack Road. 3. Turn along Ian Macdonald Boulevard and continue straight to York Lions Stadium Crossing. 4. Turn left at the crossing onto the path. 5. Continue straight on Library Lane. 6. Turn right at the fork in the path and continue around the corner. 7. Bergeron Centre is on the right.
2	1. From the rear of Bergeron, turn right and continue straight towards Campus Walk. 2. Turn right onto Campus Walk and continue straight until the Petrie Building. 3. Turn left and follow the path for one block. 4. Turn right and continue straight on the left-hand side. 5. Merge onto the road and turn left at Ottawa Road. 6. Turn right at the next stop sign. 7. Turn left at the path and continue straight until Chimneystack Road. 8. Turn left and cross Chimneystack Road to the other path. 9. Turn left onto Albany Road. 10. Turn left at 190 Albany Road.	1. Turn right onto Albany Road and follow the road. 2. Turn right onto the path adjacent to Chimneystack Road. 3. Cross Ian Macdonald Boulevard and turn right to continue on the path. 4. Turn right from the path onto the road. 5. Turn left at Ottawa Road. 6. Turn right into the parking lot, continuing straight to the path. 7. Follow the path until the Petrie Building 8. Turn left and follow the path for one block. 9. Turn right onto Campus Walk 10. Turn left after one block and continue straight. 11. Bergeron Centre is on the left.

3	1. From the rear of Bergeron, turn left onto Library Lane. 2. Turn right onto Campus Walk 3. Merge onto Vanier Lane and turn right at the end. 4. Turn left at Ian Macdonald Boulevard, 5. Turn right at Chimneystack Road, 6. Turn left at Albany Road 7. Turn left into 190 Albany Road Parking Lot	1. Turn right onto Albany Road and follow the road. 2. Turn left onto Chimneystack Road. 3. Turn right onto Vanier Lane and continue until the fork in the crescent. 4. Turn right on Campus Walk and continue until Library Lane. 5. Turn left onto Library Lane. 6. Turn right at the fork in the path and continue around the corner. 7. Bergeron Centre is on the right.
4	1. From the rear of Bergeron, turn left then right onto Library Lane and continue straight till Scholars Walk. 2. Turn right at Scholars Walk and continue straight till the Pond Road. 3. Turn left at the Pond Road and continue straight till Ian Macdonald Boulevard. 4. Turn left at Ian Macdonald Boulevard and continue straight to York Boulevard. 5. Turn right at York Boulevard and keep left. 6. Turn left into the Parking Lot and turn right before Vanier Lane. 7. Continue straight on the pathway to Severn Road. 8. Continue straight on Severn Road 9. Turn right into the 190 Albany Road Parking Lot.	1. Turn left onto Severn Road. 2. Continue straight and turn right onto Vanier Lane. 3. Continue straight on Vanier Lane until Ian Macdonald Boulevard. 4. Turn left onto Ian Macdonald Boulevard. 5. Continue straight and turn right onto the Pond Road. 6. Continue straight and turn right at Sentinel Road. 7. Turn left onto Scholars Walk and continue straight. 8. Keep left at the fork in the path until Library Lane. 9. Turn left onto Library Lane and keep right. 10. Bergeron Centre is on the right.

ECC Ride and Survey Process

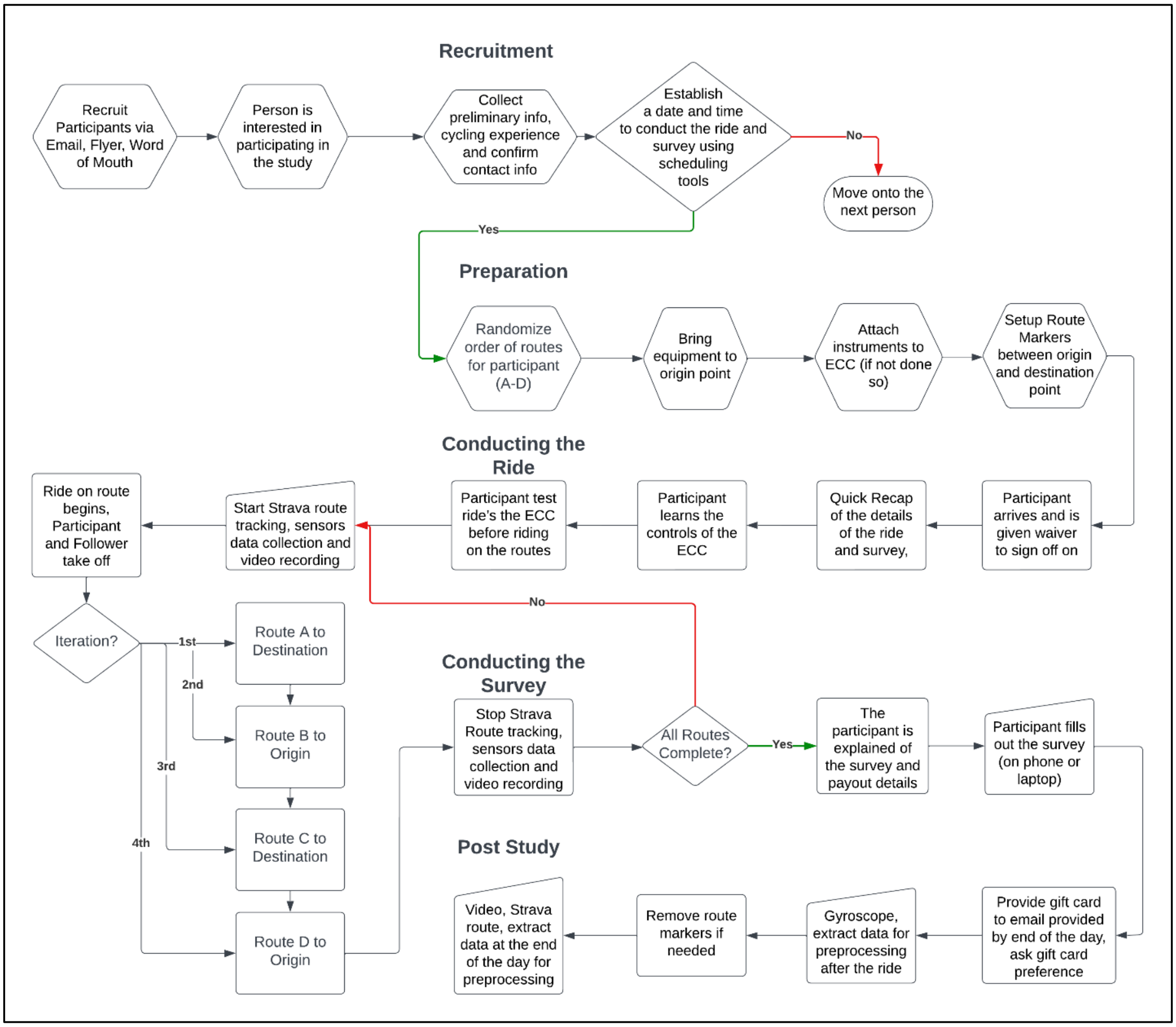

Figure A5: Flowchart of ECC Ride and Survey

ECC Study Results

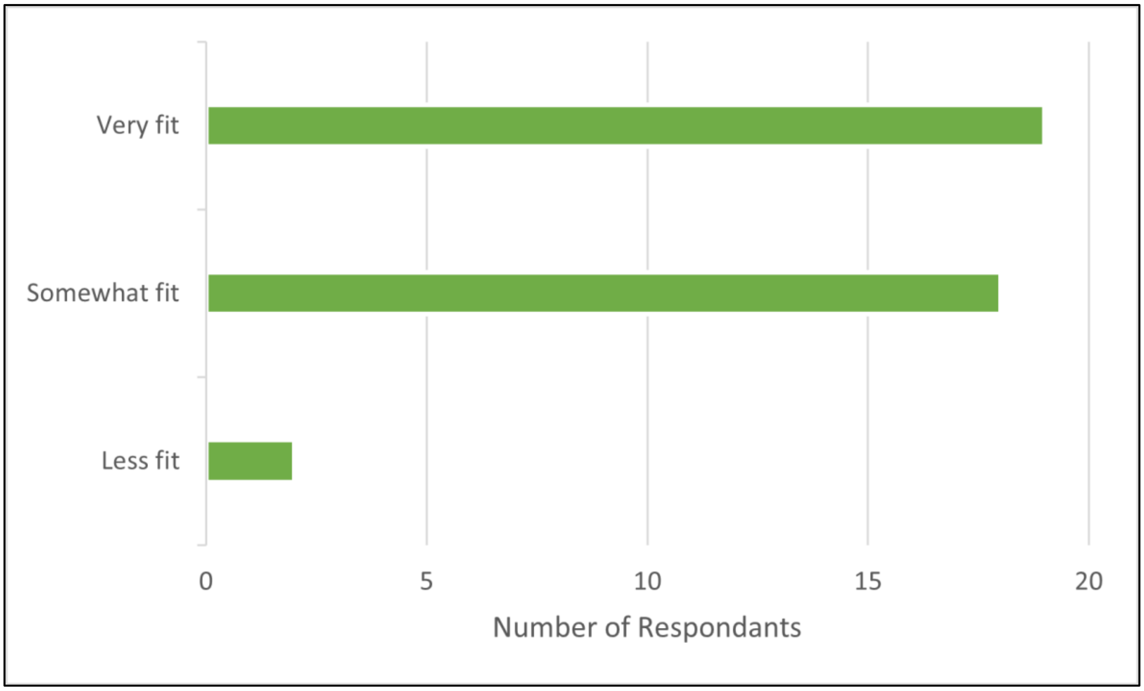

Figure A6: Physical Fitness Results

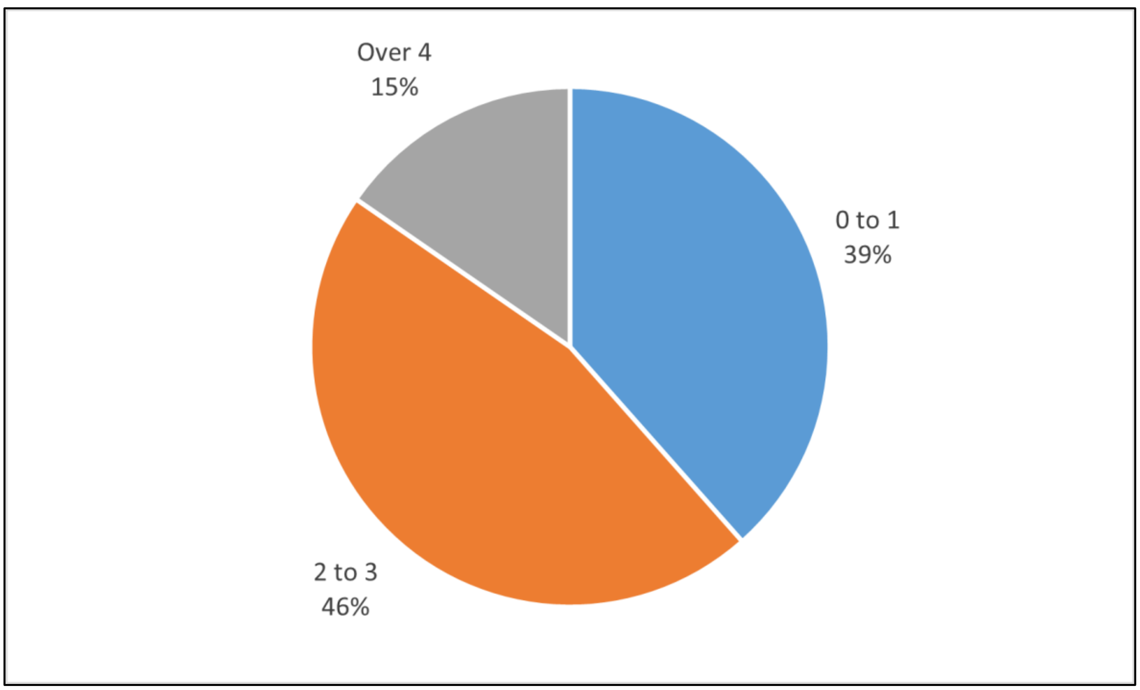

Figure A7: Number of Days in A Week Cycled

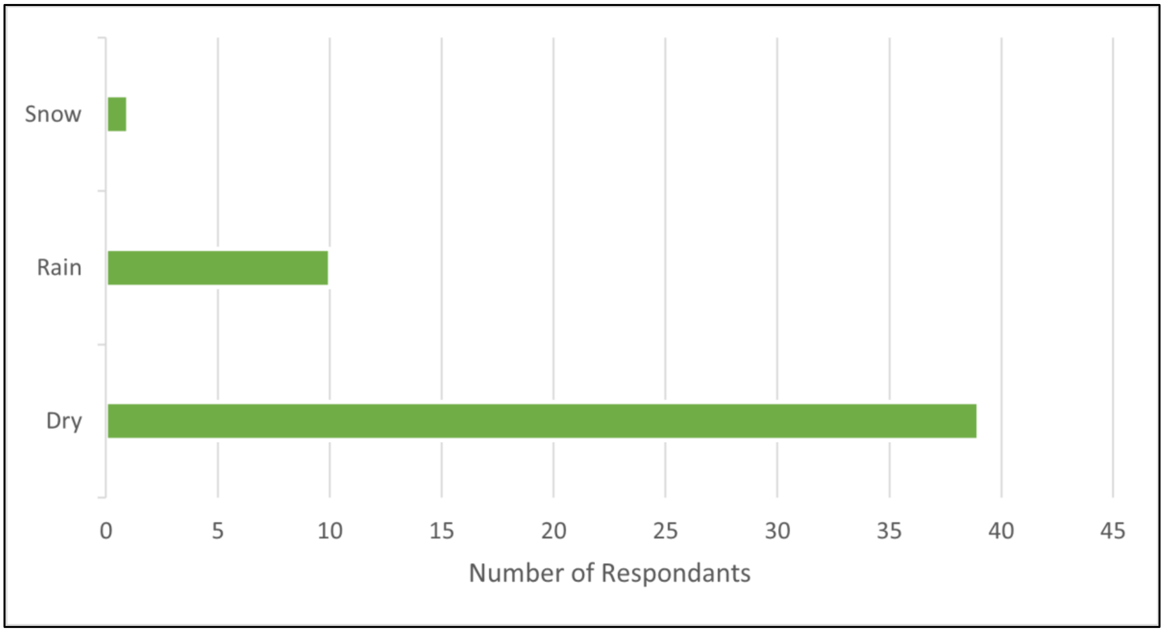

Figure A8: Weather Conditions Cycled

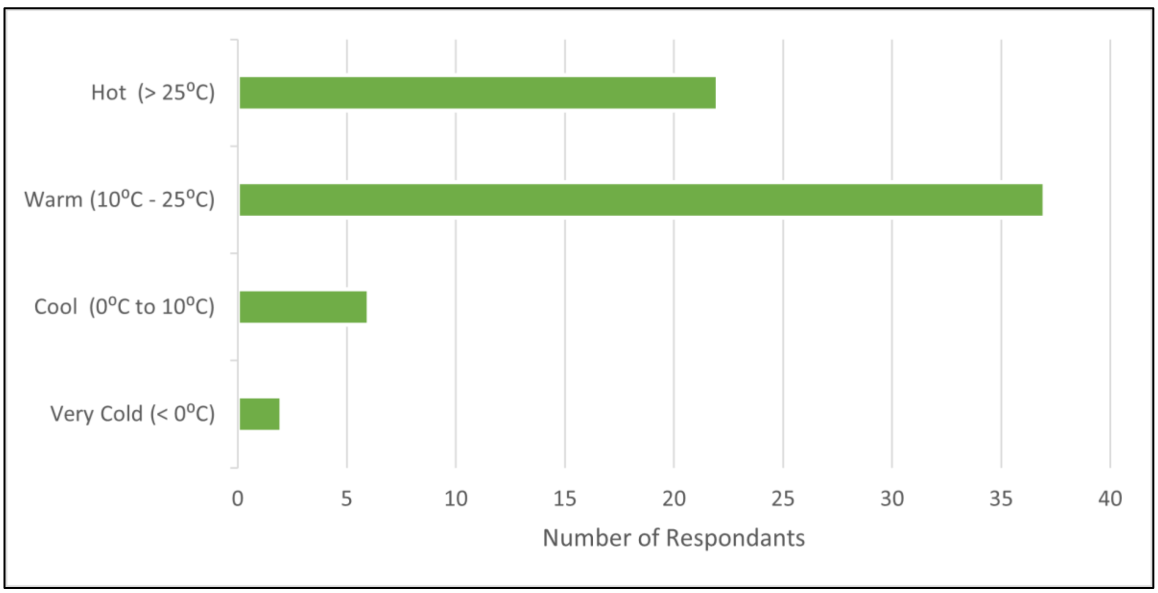

Figure A9: Temperatures Cycled

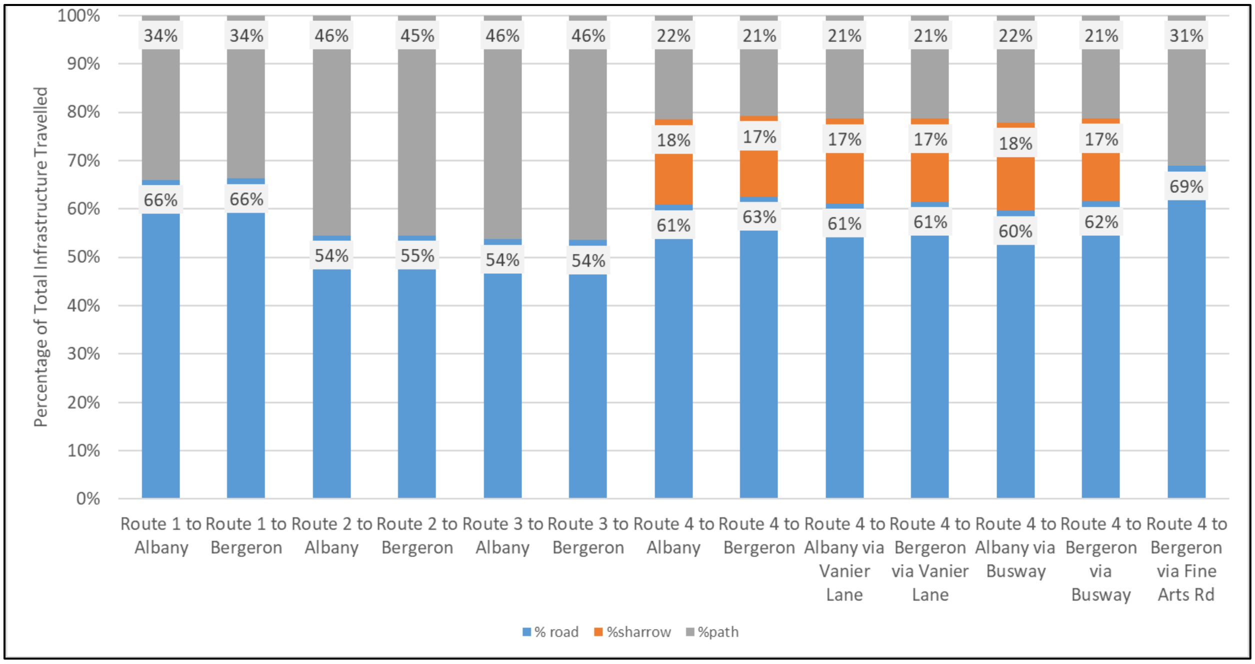

Figure A10: Route Infrastructure Proportion for All Majorly Distinct Routes

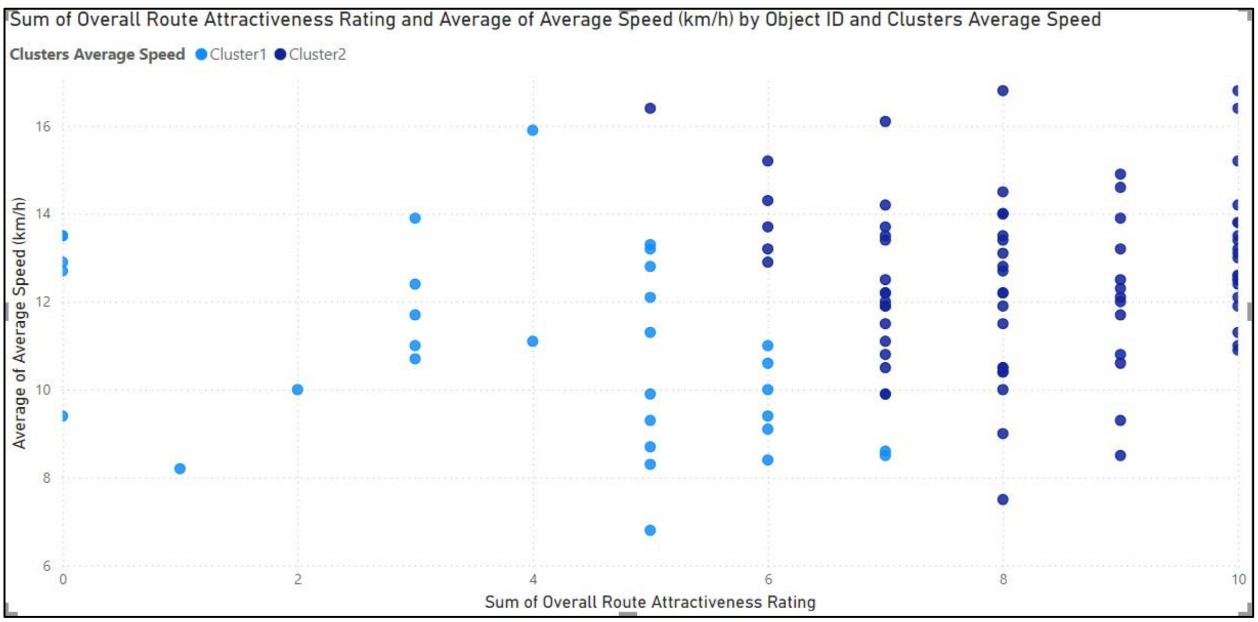

Figure A11: The clustering chart for categorizing cyclists based on average speed.

Table A2: Locations of Pavement Distress Outliers

Route ID	Destination	Location	Longitude	Latitude	Pavement Distress Type	Details
1	Albany	York Lions Stadium South Side	43.77433	-79.50685	Depression	Maintenance hole
1	Bergeron	Ian Macdonald Boulevard North of Zum Bus Stop	43.77711	-79.50113	Alligator Crack, Rutting	
1	Bergeron	Ian Macdonald Boulevard at Founders Rd East Side	43.77778	-79.50235	Alligator Crack, Rutting	
2	Albany	McLaughlin Rd at Tatham Hall East Side	43.77737	-79.50197	Tactile Pavement	Both Ways
2	Albany	McLaughlin Rd at Tatham Hall North Side	43.77735	-79.50268	Alligator Crack, Transverse Crack	
2	Albany	Petrie Science Building Northeast Entrance	43.77393	-79.50667	Depression	Maintenance hole, Both ways
2	Albany	Campus Walk at Chemistry Building	43.77325	-79.50707	Depression	Maintenance hole, Both ways
2	Albany	Campus Walk at Tim Hortons	43.77306	-79.50797	Depression	Maintenance hole, Both ways
2	Albany	Campus Walk at Tim Hortons	43.77291	-79.50792	Depression	
2	Albany	Bergeon Loading Zone	43.77185	-79.50702	Depression	Both Ways
3	Bergeron	Campus Walk at Lassonde Building	43.77370	-79.50485	Depression	Maintenance hole

Route ID	Destination	Location	Longitude	Latitude	Pavement Distress Type	Details
3	Bergeron	Campus Walk at Lassonde Building	43.77351	-79.50542	Depression	Maintenance hole
3	Albany	Campus Walk at Ross Building	43.77367	-79.50466	Depression	Maintenance hole
3	Albany	Campus Walk at Vanier Lane	43.77445	-79.50250	Depression	
3	Albany	Library Lane at Arboretum Lane South Side	43.77272	-79.50635	Depression	Both ways
3	Albany	Library Lane at Arboretum Lane North Side	43.77280	-79.50637	Depression	Both ways
3	Albany	Campus Walk at Lumbers Building	43.77401	-79.50426	Depression	Both ways
3	Albany	Campus Walk at Student Centre	43.77408	-79.50325	Depression	Maintenance hole
3	Albany	Chimneystack Road at Ian Macdonald Boulevard	43.77635	-79.50061	Alligator Crack, Transverse Crack	Both ways
3	Albany	Vanier Lane at Ian Macdonald Boulevard	43.77635	-79.50061	Patching	Both ways
4	Bergeron	Pond Road at Atkinson Road	43.77038	-79.50101	Pothole	
4	Albany	Pond Road at Ian MacDonald Boulevard	43.77110	-79.49837	Alligator Crack, Transverse Crack	
4	Albany	Scholars Walk at Osgoode Law School North Side	43.77097	-79.50390	Transverse Crack	

Route ID	Destination	Location	Longitude	Latitude	Pavement Distress Type	Details
4	Albany	Scholars Walk at Osgoode Law School South Side	43.77053	-79.50360	Patching	
4	Albany	Pond Road at Sentinel Road	43.76999	-79.50268	Longitudinal Crack	
4	Bergeron	Pond Road at Ian MacDonald Boulevard	43.77112	-79.49843	Alligator Crack	Both ways
4	Bergeron	Lower Scholars Walk at Osgoode Law School	43.77095	-79.50376	Depression	
4	Bergeron	Ian Macdonald Boulevard at Fine Arts Road	43.77242	-79.49898	Alligator Crack, Transverse Crack	

<u>AHP Weights & Categorized Results</u>

Table A3: Scenario 1 Aggregated Response Matrix

	Time	**Distance**	**Infrastructure**	**Pavement**	**Junctions**	**Risk of Collision**	**Object Frequency**	**Visibility**	**Sightlines**	**Comfort**	**Enjoyment**
Time	1.00	2.27	0.42	0.43	1.04	0.20	0.81	0.39	0.68	0.52	1.18
Distance	0.44	1.00	0.51	0.40	1.01	0.29	0.89	0.51	0.99	0.79	1.24
Infrastructure	2.40	1.95	1.00	0.65	1.40	0.21	0.71	0.45	0.67	1.18	1.28
Pavement	2.35	2.50	1.53	1.00	2.47	0.36	1.04	0.54	0.92	1.73	1.61
Junctions	0.96	0.99	0.71	0.40	1.00	0.26	0.44	0.35	0.74	0.86	1.18
Risk of Collision	5.08	3.41	4.68	2.76	3.86	1.00	3.31	2.58	3.08	4.15	4.35
Object Frequency	1.24	1.12	1.41	0.96	2.30	0.30	1.00	0.89	1.14	1.76	1.72
Visibility	2.58	1.98	2.20	1.85	2.83	0.39	1.13	1.00	1.98	2.25	2.04
Sightlines	1.47	1.01	1.50	1.09	1.36	0.32	0.87	0.50	1.00	1.28	1.51
Comfort	1.91	1.26	0.85	0.58	1.16	0.24	0.57	0.44	0.78	1.00	1.04
Enjoyment	0.85	0.81	0.78	0.62	0.85	0.23	0.58	0.49	0.66	0.97	1.00

Table A4: Scenario 2 Aggregated Response Matrix

	Time	**Distance**	**Infrastructure**	**Pavement**	**Junctions**	**Risk of Collision**	**Object Frequency**	**Visibility**	**Sightlines**	**Comfort**	**Enjoyment**
Time	1.00	2.46	0.33	0.43	0.91	0.20	0.58	0.31	0.64	0.58	1.12
Distance	0.41	1.00	0.34	0.36	0.84	0.30	0.62	0.43	0.80	0.58	0.80
Infrastructure	3.07	2.91	1.00	0.86	1.83	0.29	0.88	0.45	0.84	1.08	1.11
Pavement	2.32	2.80	1.16	1.00	3.06	0.42	1.46	0.58	1.10	1.58	1.24
Junctions	1.10	1.19	0.55	0.33	1.00	0.28	0.67	0.36	0.91	0.85	0.94
Risk of Collision	5.04	3.38	3.45	2.37	3.62	1.00	3.86	3.00	3.65	3.93	4.13
Object Frequency	1.73	1.62	1.14	0.68	1.50	0.26	1.00	0.98	1.40	2.01	2.09
Visibility	3.23	2.32	2.24	1.73	2.75	0.33	1.02	1.00	1.74	1.80	2.34
Sightlines	1.57	1.25	1.19	0.91	1.10	0.27	0.71	0.58	1.00	1.28	1.68
Comfort	1.72	1.73	0.93	0.63	1.18	0.25	0.50	0.55	0.78	1.00	1.30
Enjoyment	0.89	1.24	0.90	0.80	1.06	0.24	0.48	0.43	0.59	0.77	1.00

Table A5: Scenario 3 Aggregated Response Matrix

	Time	**Distance**	**Infrastructure**	**Pavement**	**Junctions**	**Risk of Collision**	**Object Frequency**	**Visibility**	**Sightlines**	**Comfort**	**Enjoyment**
Time	1.00	2.27	0.42	0.43	1.04	0.20	0.81	0.39	0.68	0.52	1.18
Distance	0.44	1.00	0.51	0.40	1.01	0.29	0.89	0.51	0.99	0.79	1.24
Infrastructure	2.40	1.95	1.00	0.65	1.40	0.21	0.71	0.45	0.67	1.18	1.28
Pavement	2.35	2.50	1.53	1.00	2.47	0.36	1.04	0.54	0.92	1.73	1.61
Junctions	0.96	0.99	0.71	0.40	1.00	0.26	0.44	0.35	0.74	0.86	1.18
Risk of Collision	5.08	3.41	4.68	2.76	3.86	1.00	3.31	2.58	3.08	4.15	4.35
Object Frequency	1.24	1.12	1.41	0.96	2.30	0.30	1.00	0.89	1.14	1.76	1.72
Visibility	2.58	1.98	2.20	1.85	2.83	0.39	1.13	1.00	1.98	2.25	2.04
Sightlines	1.47	1.01	1.50	1.09	1.36	0.32	0.87	0.50	1.00	1.28	1.51
Comfort	1.91	1.26	0.85	0.58	1.16	0.24	0.57	0.44	0.78	1.00	1.04
Enjoyment	0.85	0.81	0.78	0.62	0.85	0.23	0.58	0.49	0.66	0.97	1.00

Table A6: Scenario 4 Aggregated Response Matrix

	Time	Distance	Infrastructure	Pavement	Junctions	Risk of Collision	Object Frequency	Visibility	Sightlines	Comfort	Enjoyment
Time	1.00	1.48	0.42	0.19	0.57	0.17	0.48	0.46	0.64	0.26	1.07
Distance	0.68	1.00	0.41	0.21	0.50	0.22	0.59	0.31	0.57	0.28	0.67
Infrastructure	2.35	2.46	1.00	0.84	1.73	0.25	1.03	0.62	1.05	0.66	1.28
Pavement	5.20	4.83	1.18	1.00	2.10	0.35	1.70	0.72	2.66	1.50	1.36
Junctions	1.77	2.00	0.58	0.48	1.00	0.35	0.62	0.64	1.43	0.56	0.75
Risk of Collision	5.78	4.46	3.99	2.88	2.85	1.00	3.23	2.74	3.05	3.39	4.70
Object Frequency	2.06	1.71	0.97	0.59	1.61	0.31	1.00	0.89	2.02	2.02	1.97
Visibility	2.20	3.21	1.62	1.39	1.56	0.36	1.12	1.00	1.36	2.17	2.66
Sightlines	1.57	1.74	0.95	0.38	0.70	0.33	0.50	0.74	1.00	1.61	2.05
Comfort	3.90	3.60	1.51	0.67	1.79	0.30	0.50	0.46	0.62	1.00	2.49
Enjoyment	0.93	1.50	0.78	0.74	1.34	0.21	0.51	0.38	0.49	0.40	1.00

Table A7: Scenario 5 Aggregated Response Matrix

	Time	Distance	Infrastructure	Pavement	Junctions	Risk of Collision	Object Frequency	Visibility	Sightlines	Comfort	Enjoyment
Time	1.00	3.10	0.36	0.87	0.85	0.34	1.37	0.53	0.82	0.71	0.92
Distance	0.32	1.00	0.43	0.43	0.62	0.30	1.48	0.56	1.29	0.74	0.84
Infrastructure	2.79	2.32	1.00	0.68	1.45	0.25	0.92	0.57	0.50	1.25	1.05
Pavement	1.15	2.31	1.47	1.00	3.71	0.56	1.24	0.82	0.44	1.84	1.38
Junctions	1.17	1.61	0.69	0.27	1.00	0.31	0.80	0.29	0.68	0.95	0.88
Risk of Collision	2.98	3.30	4.01	1.79	3.21	1.00	4.36	4.68	3.07	4.37	3.52
Object Frequency	0.73	0.68	1.09	0.80	1.26	0.23	1.00	0.60	0.68	2.06	1.73
Visibility	1.90	1.78	1.76	1.23	3.47	0.21	1.68	1.00	1.39	1.88	1.66
Sightlines	1.22	0.78	1.99	2.26	1.47	0.33	1.47	0.72	1.00	1.72	2.40
Comfort	1.40	1.35	0.80	0.54	1.05	0.23	0.49	0.53	0.58	1.00	1.21
Enjoyment	1.09	1.19	0.96	0.72	1.13	0.28	0.58	0.60	0.42	0.83	1.00

Table A8: Enthusiast Cyclist Results

Variables	Value
Average Number of Pavement Events	6.33
Average Number of Safety Events	0.16
Average of Travel Time Rating	4.96
Average Travel Distance Rating	4.80
Average Comfort Rating	5.95
Average Enjoyment Rating	7.23
Average Safety Rating	7.25
Average Pavement Condition Rating	6.44
Average Visibility Rating	7.75
Max of Reason for Biking	6.00
Max of Temperature Biked	4.00
Max of Weather Conditions Biked	7.00
Max of Fitness Category	16.00
Max of Number of Days in a Week Biked	12.00
Max of Stops you from cycling	2.00
Max of Cycling Infrastructure avoided	0.00

Table A9: Leisure cyclist results

Variables	Value
Average Number of Pavement Events	0.69
Average Number of Safety Events	0.38
Average of Travel Time Rating	4.85
Average Travel Distance Rating	4.44
Average Comfort Rating	6.38
Average Enjoyment Rating	6.50
Average Safety Rating	6.25
Average Pavement Condition Rating	5.91
Average Visibility Rating	6.75
Max of Reason for Biking	12.00
Max of Temperatures Biked	1.00
Max of Weather Conditions Biked	3.00
Max of Fitness Category	14.00
Max of Number of Days in a Week Biked	10.00
Max of Stops you from cycling	2.00
Max of Cycling Infrastructure avoided	2.00

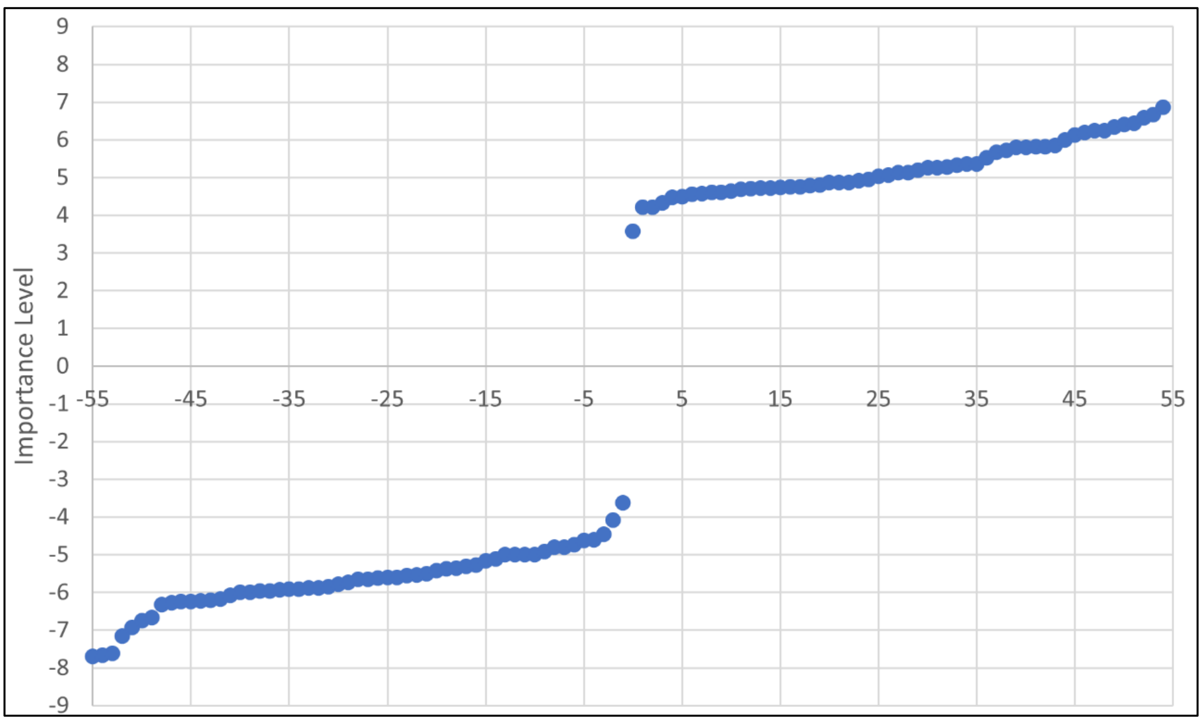

Figure A12: Averaged AHP Survey Results

Table A10: Spearman Rank Correlations for The Variables

	Comfort	Travel Time (min)	Travel Distance (km)	Average Speed (km/h)	Pavement Events	Safety Events	Junctions	Object Frequency	Travel Time Rating	Travel Distance Rating	Comfort Rating	Enjoyment Rating	Safety Rating	Pavement Condition Rating	Visibility Rating	Overall Route Attractiveness Rating
Comfort	1.00	0.50	0.23	-0.20	0.23	0.27	0.10	0.14	-0.08	-0.05	-0.05	-0.23	-0.17	-0.02	-0.13	-0.14
Travel Time (min)	0.50	1.00	0.42	-0.56	-0.25	0.14	0.16	0.25	0.07	-0.06	0.00	-0.03	-0.11	-0.05	0.00	-0.10
Travel Distance (km)	0.23	0.42	1.00	0.37	0.21	-0.08	0.09	0.28	-0.03	-0.29	0.01	0.10	0.09	0.04	0.17	0.13
Average Speed (km/h)	-0.20	-0.56	0.37	1.00	0.48	-0.17	-0.08	-0.02	-0.07	-0.15	-0.05	0.06	0.12	0.07	0.15	0.21
Pavement Events	0.23	-0.25	0.21	0.48	1.00	0.01	-0.19	-0.18	-0.09	-0.05	0.06	-0.09	0.13	0.08	-0.05	0.06
Safety Events	0.27	0.14	-0.08	-0.17	0.01	1.00	0.06	-0.04	0.04	0.14	0.04	0.02	-0.07	0.04	-0.23	-0.05
Junctions	0.10	0.16	0.09	-0.08	-0.19	0.06	1.00	0.30	-0.10	-0.18	-0.08	0.01	-0.10	-0.02	0.07	0.12
Object Frequency	0.14	0.25	0.28	-0.02	-0.18	-0.04	0.30	1.00	-0.13	-0.09	-0.09	-0.02	-0.10	-0.01	0.07	-0.13
Travel Time Rating	-0.08	0.07	-0.03	-0.07	-0.09	0.04	-0.10	-0.13	1.00	0.57	0.41	0.25	0.29	0.28	0.18	0.18
Travel Distance Rating	-0.05	-0.06	-0.29	-0.15	-0.05	0.14	-0.18	-0.09	0.57	1.00	0.16	-0.01	0.13	0.13	-0.11	0.02
Comfort Rating	-0.05	0.00	0.01	-0.05	0.06	0.04	-0.08	-0.09	0.41	0.16	1.00	0.47	0.40	0.57	0.34	0.37
Enjoyment Rating	-0.23	-0.03	0.10	0.06	-0.09	0.02	0.01	-0.02	0.25	-0.01	0.47	1.00	0.54	0.43	0.39	0.54
Safety Rating	-0.17	-0.11	0.09	0.12	0.13	-0.07	-0.10	-0.10	0.29	0.13	0.40	0.54	1.00	0.53	0.43	0.55
Pavement Condition Rating	-0.02	-0.05	0.04	0.07	0.08	0.04	-0.02	-0.01	0.28	0.13	0.57	0.43	0.53	1.00	0.37	0.56
Visibility Rating	-0.13	0.00	0.17	0.15	-0.05	-0.23	0.07	0.07	0.18	-0.11	0.34	0.39	0.43	0.37	1.00	0.48
Overall Route Attractiveness Rating	-0.14	-0.10	0.13	0.21	0.06	-0.05	0.12	-0.13	0.18	0.02	0.37	0.54	0.55	0.56	0.48	1.00

Case Study

Table A11: Case Study Data

Route ID	**1**	**2**	**3**	**4**
Route Segments Used	Eglinton-Glenholme-Rogers-Old Weston- St Clair	Eglinton-Cemetery-Rogers-Old Weston- St Clair	Eglinton-Glenholme-Rogers-Weston	Eglinton-Keele-Rogers-Weston
Cycling Infrastructure Distance (km)	2.02	2.40	2.00	0.11
Stop/Traffic control Intersections	18	16	23	22
Number of Turns	9	10	5	3
Time (min)	25	27	26	25
Distance (km)	5.5	5.9	6.4	6.1
Cycling Infrastructure %	37%	41%	31%	2%
Junctions	27	26	28	25
Final Score	6.90	7.69	3.23	4.24

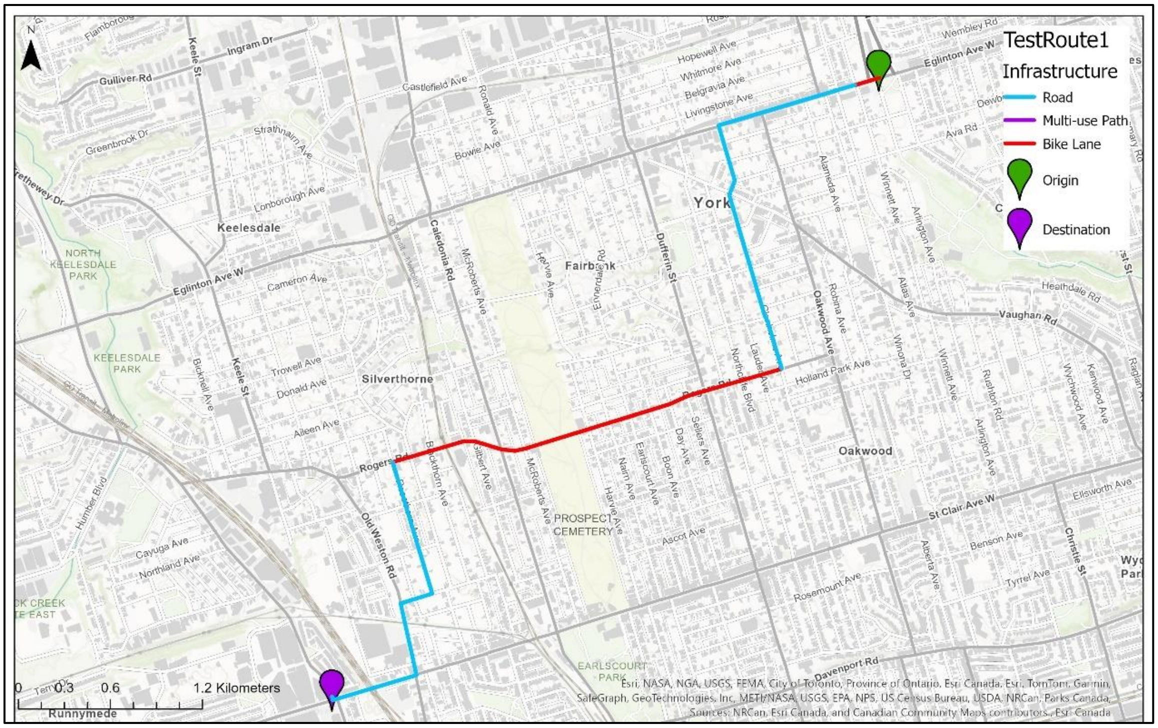

Figure A13: Test Route 1

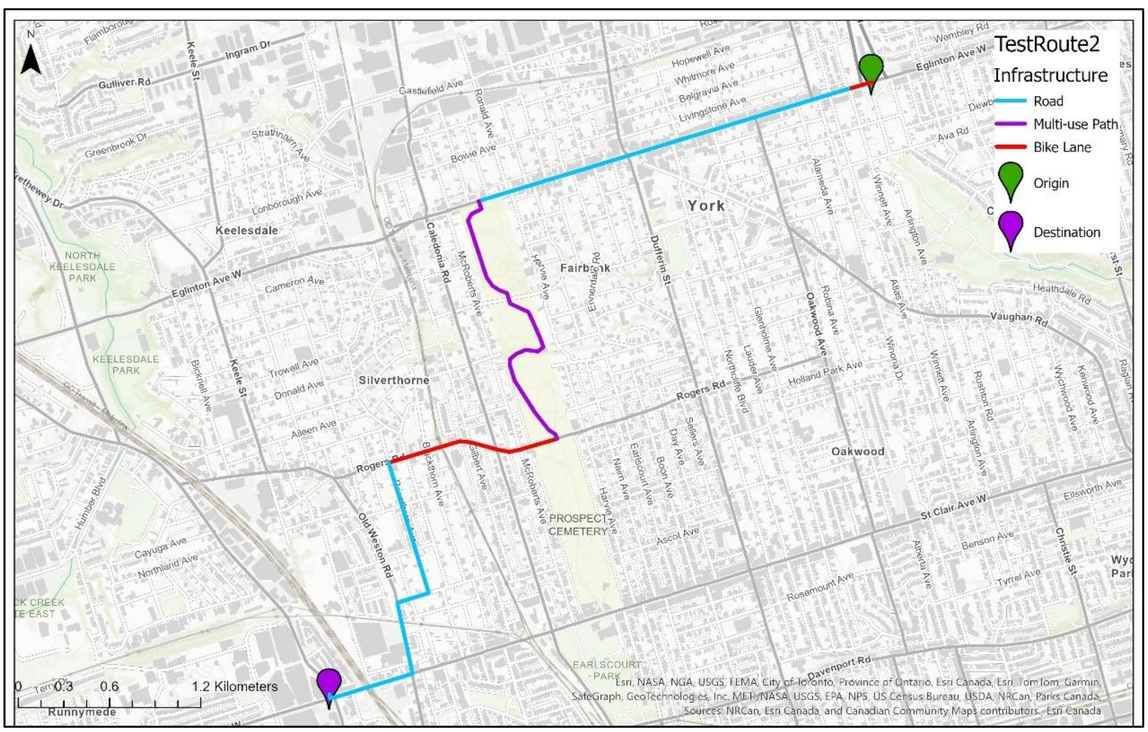

Figure A14: Test Route 2

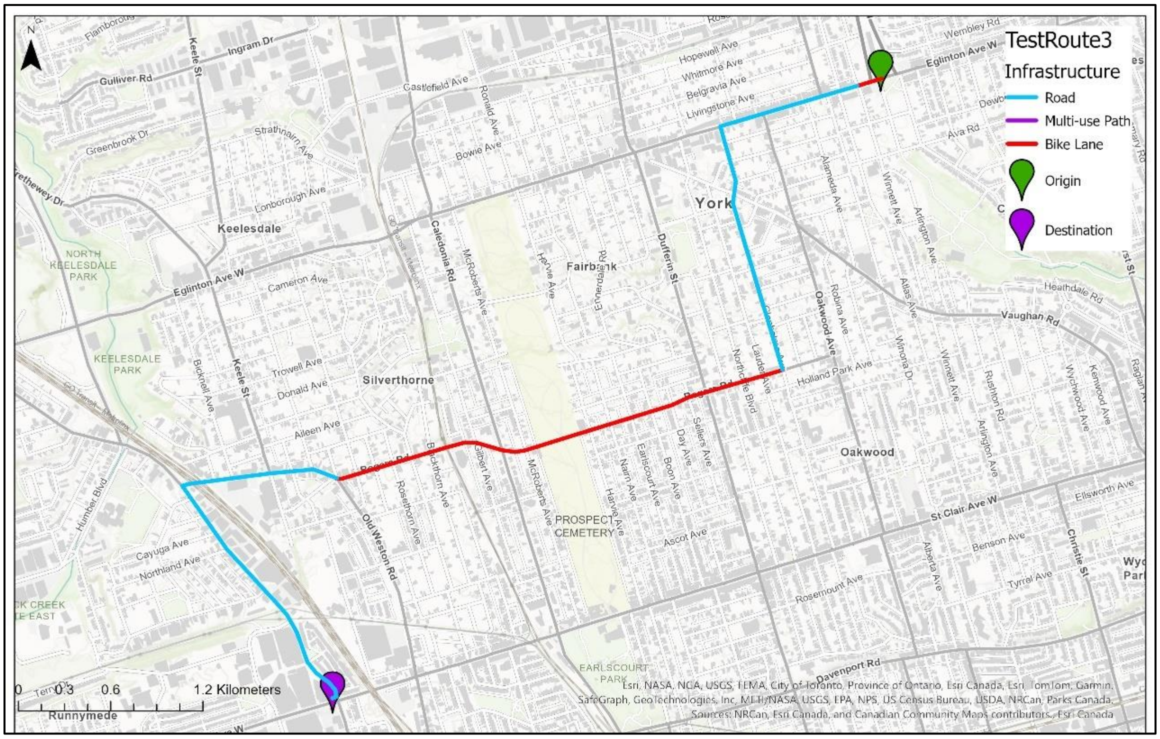

Figure A15: Test Route 3

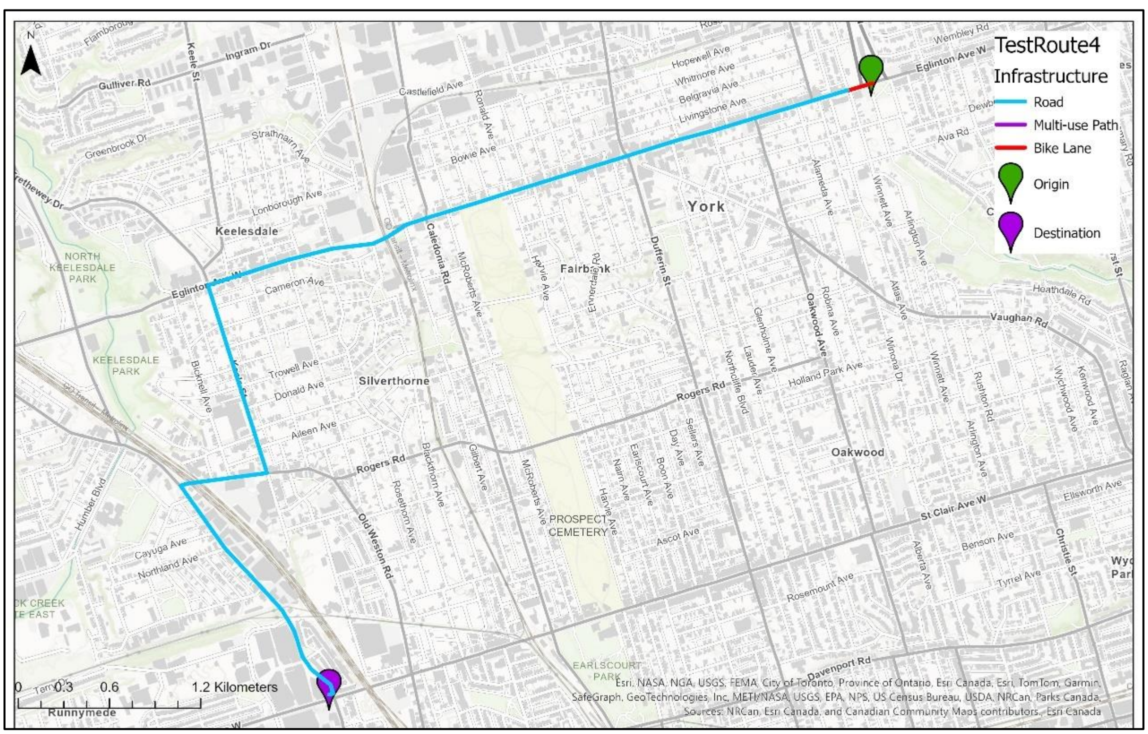

Figure A16: Test Route 4

Appendix B: Recruitment Examples

TEST RIDE AN ELECTRIC CARGO BIKE

APR/ MAY

Location:
Rear of Bergeron Centre (Garages)

2024

This study will have you ride an electric cargo cycle on four different routes between an origin and destination point within the York University Campus (8 minutes per route).

You will be given a brief rundown on how to operate the cargo cycle and the study routes (5 minutes)

After that, you will be asked to answer a short survey about your experience during the study (10 minutes).

Upon completion of both tasks, you will be awarded a $25 gift card of your choice.

Register Here!

More information, contact David

Email: david999@my.yorku.ca

APPROVED FOR POSTING ON 2024-04-19 BY

YORK UNIVERSITÉ UNIVERSITY TEMPORARY USE OF UNIVERSITY SPACE

Recruitment Email Template:

Greetings <Name>,

York University is conducting a field survey on people's route choice behaviour for electric cargo bikes.
This survey is part of a larger project funded by the Natural Sciences and Engineering Research Council (NSERC).

This field survey will be conducted at <location> on <date/time>. You will be asked to test ride an electric cargo cycle on several routes between the York University Keele Campus for approximately 8 minutes per route (up to 4 routes for around 35 minutes). You will be given 5 minutes to practice using the electric cargo cycle before cycling on the routes. The entire experience will take 1 hour. Eligible participants should be comfortable riding a bicycle. Experience using an electric cycle (E-bike) is an asset but not required. We will provide participants with instructions on the proper use of the electric cargo cycle before riding.

At the end of the ride, **you will be asked to answer a short survey about your experience using the electric cargo bike and the routes**. The data collected in this research project will be anonymized to ensure that your personal information is not associated with any of the results. This data may be used by members of the research team in subsequent research investigations exploring similar lines of inquiry.
For your participation in the study, you will be compensated with a $25 gift card from among available vendors on Amazon.ca such as Starbucks, Tim Hortons, Sephora, or Best Buy. We kindly ask you to share this message with individuals interested in participating in the study. Please contact us if you have any questions or concerns. Interested participants can contact the following individuals by email with the word "Survey" in the subject line:

Kevin Gingerich, Assistant Professor, kging@yorku.ca
David Tran, Graduate Researcher, david999@my.yorku.ca

Appendix C: Survey Questionnaire

York University Electric Cargo Bike Ride Survey Part 1

This survey is used to record your background with cycling and your experiences cycling with the Electric Cargo Cycle and on the cycling route. The information collected will be confidential and will be stored securely till the completion of the project.

* Indicates required question

Cycling Background

~4 min

1. Name (Will be removed once submitted) (ONLINE ONLY SUBMISSION) *

2. Study Identifier (IN PERSON ONLY SUBMISSION)

3. What is your Age *

4. What is your Gender *

   Mark only one oval.

   - Male
   - Female
   - Non-Binary
   - Gender not listed
   - Prefer not to Say

5. How would you rate your overall physical fitness? *

   //find a better rating system

   Mark only one oval.

   - 1 - minimally active
   - 2
   - 3 - somewhat active
   - 4
   - 5 - very active

6. Why do you ride a bike? *

   Check all that apply.

   - [ ] Leisure/Fun
   - [ ] Commute to Work/School
   - [ ] Shopping/Goods Transport
   - [ ] Competitive/Sport
   - [ ] Exercise
   - [ ] I don't ride a bike regularly
   - [ ] Other: ______

7. How many days in a typical week do you ride a bike? *

   Mark only one oval.

   - 0 days
   - 1-2 days
   - 3-4 days
   - 5-7 days

8. Do you bike during certain weather conditions (check all that apply) *

Check all that apply.

- [ ] Dry Weather
- [ ] Rain
- [ ] Snow/Ice

9. Do you bike during certain temperatures (check all that apply) *

Check all that apply.

- [ ] Very Cold < 0 C
- [ ] Cold Temperature 0 - 10 C
- [ ] Temperate/Cool Temperature 10 - 25 C
- [ ] Hot temperature > 25 C

10. What stops you from riding a bike more often (check all that apply) *

Check all that apply.

- [ ] Winter Weather
- [ ] Lack of Dedicated Bike Infrastructure
- [ ] Destinations are too far
- [ ] Lack of Bicycle Parking
- [ ] Lack of Shower/Changing Facilities
- [ ] Limited Physical Capabilities
- [ ] Not interested in Biking
- [ ] Other: ______________________

11. What type of Cycling Infrastructure would you avoid using? *

Check all that apply.

- [ ] Road
- [ ] Painted Bike Lane or Sharrow
- [ ] Barrier Protected Bikelane
- [ ] Multi-Use Path
- [ ] Sidewalk

12. What kind of bike(s) do you typically ride? (check all that apply) *

Check all that apply.

- [ ] Road bike (Thin Tires) with no electric assist
- [ ] Road bike (Thin Tires) with electric assist
- [ ] Trail Bike (Thick Tires) with no electric assist
- [ ] Trail Bike (Thick Tires) with electric assist
- [ ] Multi passenger or Cargo Bike with no electric assist
- [ ] Multi passenger or Cargo Bike with electric assist
- [ ] BMX/Racing
- [ ] I don't normally bike
- [ ] Other: ______________________

13. How familiar are you with electric assist bikes? *

Mark only one oval.

	0	1	2	3	4	5	
Not	◯	◯	◯	◯	◯	◯	Very familiar

14. How familiar are you with tricycle style bikes (excluding training wheels) *

Mark only one oval.

	0	1	2	3	4	5	
Not	◯	◯	◯	◯	◯	◯	Very familiar

ID:

1. Rank the routes based on travel time

Mark only one oval per row.

	0 - Longest	1	2	3 - Slightly more	4	5	6	7 - Slightly less	8	9	10 - Shortest
Route 1											
Route 2											
Route 3											
Route 4											

2. Rank the routes based on travel distance

Mark only one oval per row.

	0 - Longest	1	2	3 - Slightly more	4	5	6	7 - Slightly less	8	9	10 - Shortest
Route 1											
Route 2											
Route 3											
Route 4											

3. Rank the routes based on Comfort *

Mark only one oval per row.

	0 - Least	1	2	3 - Slightly less	4	5	6	7 - Slightly more	8	9	10 - Most
Route 1											
Route 2											
Route 3											
Route 4											

4. Rank the routes based on Enjoyment while riding *

Mark only one oval per row.

	0 - Least	1	2	3 - Slightly less	4	5	6	7 - Slightly more	8	9	10 - Most
Route 1											
Route 2											
Route 3											
Route 4											

ID:

5. Rank the routes based on the Feeling of Safety while riding *

Mark only one oval per row.

	0 - Least	1	2	3 - Slightly less	4	5	6	7 - Slightly more	8	9	10 - Most
Route 1											
Route 2											
Route 3											
Route 4											

6. Rank the routes based on the Pavement Condition *

Mark only one oval per row.

	0 - Least	1	2	3 - Slightly less	4	5	6	7 - Slightly more	8	9	10 - Most
Route 1											
Route 2											
Route 3											
Route 4											

7. Rank the routes based on how well you can see vehicles, people and objects (sightlines) *

Mark only one oval per row.

	0 - Least	1	2	3 - Slightly less	4	5	6	7 - Slightly more	8	9	10 - Most
Route 1											
Route 2											
Route 3											
Route 4											

8. How would you rate the attractiveness of each route for cycling? *

Mark only one oval per row.

	0 - Least	1	2	3 - Slightly less	4	5	6	7 - Slightly more	8	9	10 - Most
Route 1											
Route 2											
Route 3											
Route 4											

ID:

9. Would you ever cycle on the route for work or leisure again? *

Mark only one oval per row.

	Yes	No
Route 1	◯	◯
Route 2	◯	◯
Route 3	◯	◯
Route 4	◯	◯

10. Is this route different than what you usually take to travel between these places by walking? *

Mark only one oval.

◯ Yes
◯ No
◯ I have never travelled to/from this place by walking

#11: Please put a number over each circle. 1 = equal importance, 3 = slightly more important, 5 = noticeably more important, 7 = strongly more important, 9 = significantly more important (CANNOT HAVE THE SAME NUMBER FOR EACH CIRCLE!)

11. Which of the two factors in each row do you value more for an attractive cycling route? *

Mark only one oval per row.

	First Factor	Second Factor
Travel Time or Travel Distance	◯	◯
Travel Time or Cycling Infrastructure	◯	◯
Travel Time or Pavement Condition	◯	◯
Travel Time or Intersections and Turns	◯	◯
Travel Time or Risk of Collision	◯	◯
Travel Time or Passing Vehicles and Pedestrians	◯	◯
Travel Time or the Cyclist's Visibility	◯	◯
Travel Time or Intersection Sightlines	◯	◯
Travel Time or Comfort	◯	◯
Travel Time or Enjoyment	◯	◯

	First Factor	Second Factor
Travel Distance or Cycling Infrastructure	◯	◯
Travel Distance or Pavement Condition	◯	◯
Travel Distance or Intersections and Turns	◯	◯
Travel Distance or Risk of Collision	◯	◯
Travel Distance or Passing Vehicles and Pedestrians	◯	◯
Travel Distance or Cyclist's Visibility	◯	◯
Travel Distance or Intersection Sightlines	◯	◯
Travel Distance or Comfort	◯	◯
Travel Distance of Enjoyment	◯	◯

	First Factor	Second Factor
Cycling Infrastructure or Pavement Condition	◯	◯
Cycling Infrastructure or Intersections and Turns	◯	◯
Cycling Infrastructure or Risk of Collision	◯	◯
Cycling Infrastructure or Passing Vehicles and Pedestrians	◯	◯
Cycling Infrastructure or Cyclist's Visibility	◯	◯
Cycling Infrastructure or Intersection Sightlines	◯	◯
Cycling Infrastructure or Comfort	◯	◯
Cycling Infrastructure or Enjoyment	◯	◯

	First Factor	Second Factor
Pavement Condition or Intersections and Turns	◯	◯
Pavement Condition or Risk of Collision	◯	◯
Pavement Condition or Passing Vehicles and Pedestrians	◯	◯
Pavement Condition or Cyclist's Visibility	◯	◯
Pavement Condition or Intersection Sight Distance	◯	◯
Pavement Condition or Comfort	◯	◯
Pavement Condition or Enjoyment	◯	◯

ID:

#11: Please put a number over each circle. 1 = equal importance, 3 = slightly more important, 5 = noticeably more important, 7 = strongly more important, 9 = significantly more important (CANNOT HAVE THE SAME NUMBER FOR EACH CIRCLE!)

	First Factor	Second Factor
Intersections and Turns or Risk of Collision		
Intersections and Turns or Passing Vehicles and Pedestrians		
Intersections and Turns or Cyclist Visibility		
Intersections and Turns or Intersection Sight Distance		
Intersections and Turns or Comfort		
Intersections and Turns or Enjoyment		

	First Factor	Second Factor
Risk of Collision or Passing Vehicles and Pedestrians		
Risk of Collision or Cyclist Visibility		
Risk of Collision or Intersection Sight Distance		
Risk of Collision or Comfort		
Risk of Collision or Enjoyment		

	First Factor	Second Factor
Passing Vehicles and Pedestrians or Cyclist Visibility		
Passing Vehicles and Pedestrians or Intersection Sight Distance		
Passing Vehicles and Pedestrians or Comfort		
Passing Vehicles and Pedestrians or Enjoyment		
Cyclist Visibility or Intersection Sight Distance		
Cyclist Visibility or Comfort		
Cyclist Visibility or Enjoyment		
Intersection Sight Distance or Comfort		
Intersection Sight Distance or Enjoyment		
Comfort or Enjoyment		

ID:

12. Which route of the two routes in each row is better regarding Travel Time? *

Mark only one oval per row.

	First Route	Second Route
Route 1 & 2	⬭	⬭
Route 1 & 3	⬭	⬭
Route 1 & 4	⬭	⬭
Route 2 & 3	⬭	⬭
Route 2 & 4	⬭	⬭
Route 3 & 4	⬭	⬭

13. Which route of the two routes in each row is better regarding Travel Distance? *

Mark only one oval per row.

	First Route	Second Route
Route 1 & 2	⬭	⬭
Route 1 & 3	⬭	⬭
Route 1 & 4	⬭	⬭
Route 2 & 3	⬭	⬭
Route 2 & 4	⬭	⬭
Route 3 & 4	⬭	⬭

14. Which route of the two routes in each row is better regarding Pavement Condition? *

Mark only one oval per row.

	First Route	Second Route
Route 1 & 2	⬭	⬭
Route 1 & 3	⬭	⬭
Route 1 & 4	⬭	⬭
Route 2 & 3	⬭	⬭
Route 2 & 4	⬭	⬭
Route 3 & 4	⬭	⬭

ID:

15. Which route of the two routes in each row is better regarding Bike Infrastructure? *

Mark only one oval per row.

	First Route	Second Route
Route 1 & 2	⬭	⬭
Route 1 & 3	⬭	⬭
Route 1 & 4	⬭	⬭
Route 2 & 3	⬭	⬭
Route 2 & 4	⬭	⬭
Route 3 & 4	⬭	⬭

16. Which route of the two routes in each row is better regarding Intersections and Turning? *

Mark only one oval per row.

	First Route	Second Route
Route 1 & 2	⬭	⬭
Route 1 & 3	⬭	⬭
Route 1 & 4	⬭	⬭
Route 2 & 3	⬭	⬭
Route 2 & 4	⬭	⬭
Route 3 & 4	⬭	⬭

17. Which route of the two routes in each row is better regarding Near Misses and Collisions? *

Mark only one oval per row.

	First Route	Second Route
Route 1 & 2	⬭	⬭
Route 1 & 3	⬭	⬭
Route 1 & 4	⬭	⬭
Route 2 & 3	⬭	⬭
Route 2 & 4	⬭	⬭
Route 3 & 4	⬭	⬭

ID:

18. Which route of the two routes in each row is better regarding Passing vehicles and/or Pedestrians? *

Mark only one oval per row.

	First Route	Second Route
Route 1 & 2	◯	◯
Route 1 & 3	◯	◯
Route 1 & 4	◯	◯
Route 2 & 3	◯	◯
Route 2 & 4	◯	◯
Route 3 & 4	◯	◯

19. Which route of the two routes in each row is better regarding the Visibility of road users and infrastructure? *

Mark only one oval per row.

	First Route	Second Route
Route 1 & 2	◯	◯
Route 1 & 3	◯	◯
Route 1 & 4	◯	◯
Route 2 & 3	◯	◯
Route 2 & 4	◯	◯
Route 3 & 4	◯	◯

20. Which route of the two routes in each row is better regarding sightlines(seeing objects from far distances to know what to do ?

Mark only one oval per row.

	First Route	Second Route
Route 1 & 2	◯	◯
Route 1 & 3	◯	◯
Route 1 & 4	◯	◯
Route 2 & 3	◯	◯
Route 2 & 4	◯	◯
Route 3 & 4	◯	◯

ID:

21. Which route of the two routes in each row is better regarding Comfort? *

Mark only one oval per row.

	First Route	Second Route
Route 1 & 2	◯	◯
Route 1 & 3	◯	◯
Route 1 & 4	◯	◯
Route 2 & 3	◯	◯
Route 2 & 4	◯	◯
Route 3 & 4	◯	◯

22. Which route of the two routes in each row is better regarding Enjoyment? *

Mark only one oval per row.

	First Route	Second Route
Route 1 & 2	◯	◯
Route 1 & 3	◯	◯
Route 1 & 4	◯	◯
Route 2 & 3	◯	◯
Route 2 & 4	◯	◯
Route 3 & 4	◯	◯

York University Electric Cargo Bike Ride Survey Part 3

This survey is used to record your background with cycling and your experiences cycling with the Electric Cargo Cycle and on the cycling route. The information collected will be confidential and will be stored securely till the completion of the project.

* Indicates required question

Skip to question 1Skip to question 1

Your Experience with the Electric Cargo Bike (Descriptive Experience)

For the participants reference. Questions may be answered verbally to the facilitator.

1. Identifier (Ask Survey Facilitator) *

2. Approximately how many near misses did you encounter with another vehicle or object. Briefly explain the worst near miss you have experienced on the ride (if applicable). At the end, Either show on a map, write or upload a map of where did these near misses or collisions occur. *

3. What factors did you like/not like about the routes? ~ 1min *

   List of Factors: Travel Time, Distance, Pavement Condition, Cycling Infrastructure, Intersections & Turns, Near Miss & Collisions, Passing vehicles and/or Pedestrians, Visibility of Road users and Infrastructure, Enjoyable route (presence of nature/quietness), Comfort

4. If you were a courier/delivery driver what would make you more willing to use an Electric Cargo Cycle in the future instead of a delivery van and why? *

Appendix D: Ordered Logit Model Code

Models estimated using NLOGIT software.

Model 1 Code:

```
OLOGIT
;Lhs = OVERALL
;Choices = 0,1,2,3,4,5,6,7,8,9,10
;Rhs = ONE,DISCOMFORT,TIME,SPEED,PAVEMENT,SAFETY,TURNS,OBJECTS,ROUTE4
;Panel; Fixed Effects$
```

Model 2 Code:

```
OLOGIT
;Lhs = OVERALL
;Choices = 0,1,2,3,4,5,6,7,8,9,10
;Rhs = ONE,OBJECT_FREQUENCY,R4
;Panel; Fixed Effects$
```

Model 3 Code:

```
OLOGIT
;Lhs = OVERALL
;Choices = 0,1,2,3,4,5,6,7,8,9,10
;Rhs = ONE,TIME RATING,DISTANCE RATING,COMFORT RATING,ENJOYMENT
RATING,SAFETY RATING,PAVEMENT RATING,VISIBILITY RATING, ROUTE4
;Panel; Fixed Effects$
```

Model 4 Code:

```
OLOGIT
;Lhs = OVERALL
;Choices = 0,1,2,3,4,5,6,7,8,9,10
;Rhs = ONE,ENJOYMENT RATING,SAFETY RATING,VISIBILITY RATING, ROUTE4
;Panel; Fixed Effects$
```