



Factors influencing e-cargo bike mode choice for small businesses

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ABSTRACT

As a viable alternative to traditional and electric cars and vans, e-cargo bikes have the potential to improve the sustainability of urban logistics operations, particularly for last-mile deliveries. In this study, e-cargo bike trips are modelled from a small business pilot rental scheme, and the effects of identified variables of: a) trip length and b) rainfall conditions on the attractiveness of e-cargo bikes as a mode of goods delivery are assessed. For the study, an intelligent modelling framework consisting of a) Data Acquisition System, b) Intelligent Learning Unit, and c) Output Unit is built. The effectiveness of the learning system is evaluated through its application as a case study in Dublin, Ireland. It is discovered that small businesses prefer e-cargo bikes for goods delivery over longer distances in warmer and drier weather conditions. There is a strong interaction effect between weather and distance. A drop in temperature exacerbates the deterring effect of the wet weather, making e-cargo bikes less appealing as a mode of goods delivery for small businesses. Following weather conditions, the critical variable influencing trip length is trip hour, a spatial variable used in the study as a lurking variable representing the traffic flow peak. The study concludes a strong joint effect of wet weather and temperature that affects the attractiveness of e-cargo as a mode of small business goods delivery. The study demonstrates the benefit of using a hybrid modelling framework in trip and mode choice modelling for sustainable logistics modes.

1. Introduction

Available in a variety of forms in the modern day [1], the use of cycles designed explicitly for the transport of goods has occurred as early as the 1880s. Historically, these “cargo cycles” were used for a variety of functions, such as the delivery of newspapers, post, and food, as well as street vending [2]. However, use of cargo cycles declined with the advent of automobility and the decrease in customer delivery as a business practice. Recently, cargo cycles are again rising to prominence once again due to their potential in delivering a sustainable transportation system and a green future. More importantly, these are increasingly being viewed as a potential vehicle for goods transport in response to transformed patterns of shopping and increased interest in sustainable logistics [2]. This is recognized by “New EU Urban Mobility Framework” [3], that explicitly refers to the possible value of cargo cycles as a vehicle for moving goods more sustainably in and through urban areas. Interestingly, they note how the demand for last-mile home delivery is increasing through the rising practice of shopping online across the European Union. Indeed, there have been many European countries trialling cargo cycle schemes to promote more sustainable

logistics, such as Germany, Italy, Austria, Spain, the United Kingdom, and Sweden [4].

Outside of the policy sphere, there is an (arguably greater) drive within the EU private sector for the mainstream integration of cargo cycles into urban logistics operations [5]. From a socio-technical transitions perspective [6], while cargo cycles are currently at the level of niche innovation, this private sector effort represents an industry push from below for greater integration of cargo cycles into broader logistics regimes. There is an increase in policy-maker and local authority engagement to help support, grow and legitimise such innovation – such as the electric cargo cycle trail upon which this study is based [7].

As a particularly niche innovation, electrically-assisted cargo cycles might offer an avenue for faster, farther, heavier, and easier cycle goods transport compared to traditional cargo cycles, thereby expanding the scope of cargo cycles as a vehicular substitute in logistics operations [8]. E-cargo bikes is a promising way to decarbonise a significant proportion of last-mile deliveries as a vehicular substitute to vans and cars. Modelling various scenarios of electric cargo cycle use for Munich, Germany, Llorca and Moeckel [9] reported that electric cargo cycles for last-mile delivery could reduce total carbon emissions, primarily by reducing the total distance travelled by diesel van alternatives.

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Nomenclature

SDG	Sustainable Development Goal
e-bikes	Electric bikes
DLR	Dún Laoghaire-Rathdown
BP	Back Propagation
S_s	Sum of squares
T	Magnitude of weighted connection between neurons in deep learning
L_a	Activation of the <i>ath</i> output neuron
Df	Degree of freedom
\bar{X}	mean
O_f	Observed value
E_f	Expected value
χ^2	Chi-square statistic
V	Cramer V statistic

Similarly, modelling various substitution scenarios for Porto, Portugal, Melo and Baptista [10] reported that replacing van and truck logistics journeys with electric cargo cycles could result in carbon emission reductions of up to 73% at full market penetration.

Alongside the potential carbon emissions impact of e-cargo bike logistics, broader metrics of logistics performance have also been examined [1,9–12]. Depending on the context and journey type, e-cargo bikes have been found to have a substitution potential of up to 68% for car deliveries [12] and 55% for van deliveries [9], while (cargo cycles in general) likely offering competitive commercial journey times relative to cars [1], particularly when the superiority of e-cargo bikes in terms of urban dwell times and travel distances relative to urban delivery vehicles is considered [11]. With increasing urban congestion in many cities and decreasing motor-vehicle access, Gruber and Narayanan [1] argue that cargo cycle times are likely to become more competitive in the future.

The factors influencing both the uptake and use of cargo cycles in general [13–17] and electric cargo cycles in particular [12,18,19] have also been investigated. One prominent field of inquiry in this area investigates the factors that influence the willingness to trial/use electric cargo cycles, intention to purchase and actual purchase of electric cargo cycles (i.e. uptake) [12,18,19]. This body of work analysed survey data gathered from messengers [12,18] and cargo cycle trail participants [19] in Germany. Among messengers, lower age, male gender, lower income, and higher education were associated with greater willingness to trial/use an e-cargo bike [12,18], while higher age and income were associated with the rejection of e-cargo bikes as a messenger mode [18]. In a study of cargo bike (mainly e-cargo bike) trials, Narayanan et al. [19] report that e-cargo bike purchase decisions were significantly associated with higher levels of average daily cargo cycle distance; trailing during the winter; perceiving that cargo cycles offer operational, “soft” and cost benefits; and a perception that conditions for normal commercial vehicles were deteriorating. On the other hand, there was a statistically significant decrease in the decision to purchase a cargo cycle following the trial with larger organisational catchment areas for commercial cargo cycle trips – thereby indicating the importance of commercial trip density.

Research has also been carried out more broadly to identify the enablers and constraints for cargo cycle uptake and use from groups with significant expertise and experience with cycle logistics [13,15–17]. Overall, many constraints related to non-electric cargo cycles [15]: problems with weight, low cargo capacity, difficulty cycling uphill [13], and legal regulations on electric cargo cycle max weight [16]. Infrastructure was a factor raised that can constitute a critical enabler or constraint [13,15–17], along with regulations on vehicular transport modes in terms of access, parking, tolls and taxation relative to cargo

cycles [13,15]. The development of urban consolidation centres in particular was widely cited as a critical enabler for cargo cycle adoption and success [13,16] along with transport infrastructure that caters for the unique characteristics of cargo cycles [16,17].

In light of the reviewed research examining the substitution potential of electric cargo cycles and the factors that influence cargo cycle uptake and use, the paper appears to be the first study in this area that uses observed GIS data to investigate how various factors such as journey length, temperature, rainfall, and time/day/month of use influence actual electric cargo cycle use among a small sample of eCargobike trail participants using this mode primarily for last-mile delivery and service trips. In particular, developing and using an intelligent modelling framework specifically designed for the study, we examine patterns of eCargobike use from local business participants in relation to the above variables. In this way, the aim of this study is to investigate critical determinants of eCargobike use among small business pilot participants using detailed Geographic Information System (GIS) tracker journey data and weather data gathered during the pilot scheme. The specific research questions for this study are.

- 1.1. How does trip length vary depending upon the following variables:
 1. Day maximum temperature
 2. Flow conditions that are represented by Trip Hour, Month and Day.
 3. Rainfall in mm
 4. Trip on Weekday/Weekend
- 1.2. How does a trip in rainfall vary depending upon the following variables:
 1. Day maximum temperature
 2. Flow conditions that are represented by Trip Hour, Month and Day.
 3. Trip length
 4. Trip on Weekday/Weekend

With these objectives in mind, we intend to model e-cargo bike trips and comprehend the impact of varied trip lengths and weather conditions on the decision of small businesses to complete their goods delivery using an e-cargo bike.

2. Study context

The context of this study is Dún Laoghaire-Rathdown (DLR), which is an electoral county of Dublin, Ireland, situated in the province of Leinster. Examining available data for cycling in Dublin in general, cycling journeys as a percentage of total journeys is reported as 3.4% in 2019 [20] and, at present, there is a lack of well-developed cycling infrastructure within the county [21]. However, during the pandemic, numerous temporary cycling infrastructures were constructed and designated across the city, thereby enhancing its cyclability [22]; a similar process took place in DLR county with the construction of a 3.6 km stretch of dedicated two-way cycling infrastructure – the “Coastal Mobility Route” [23] – with evidence of increased and more diverse cycling following the implementation of this facility [24]. Building on this progress, further major cycle infrastructure developments are being planned in the county with a route described as the “DLR Connector” in the pre-design stage at present; this project aims to connect villages and neighbourhoods across the county through the provision of high-quality cycling route [25]. In this way, the cyclability of the context for this study is positively evolving at present. A map of the county is displayed in Fig. 1.

The eCargobike Pilot Scheme upon which this study is based is a collaborative initiative between an Irish local authority (Dun Laoghaire-Rathdown County Council), a leading dockless bike share operator (Beeper), Smart Dún Laoghaire, and numerous local Dun Laoghaire-Rathdown small businesses and companies. The scheme enabled local

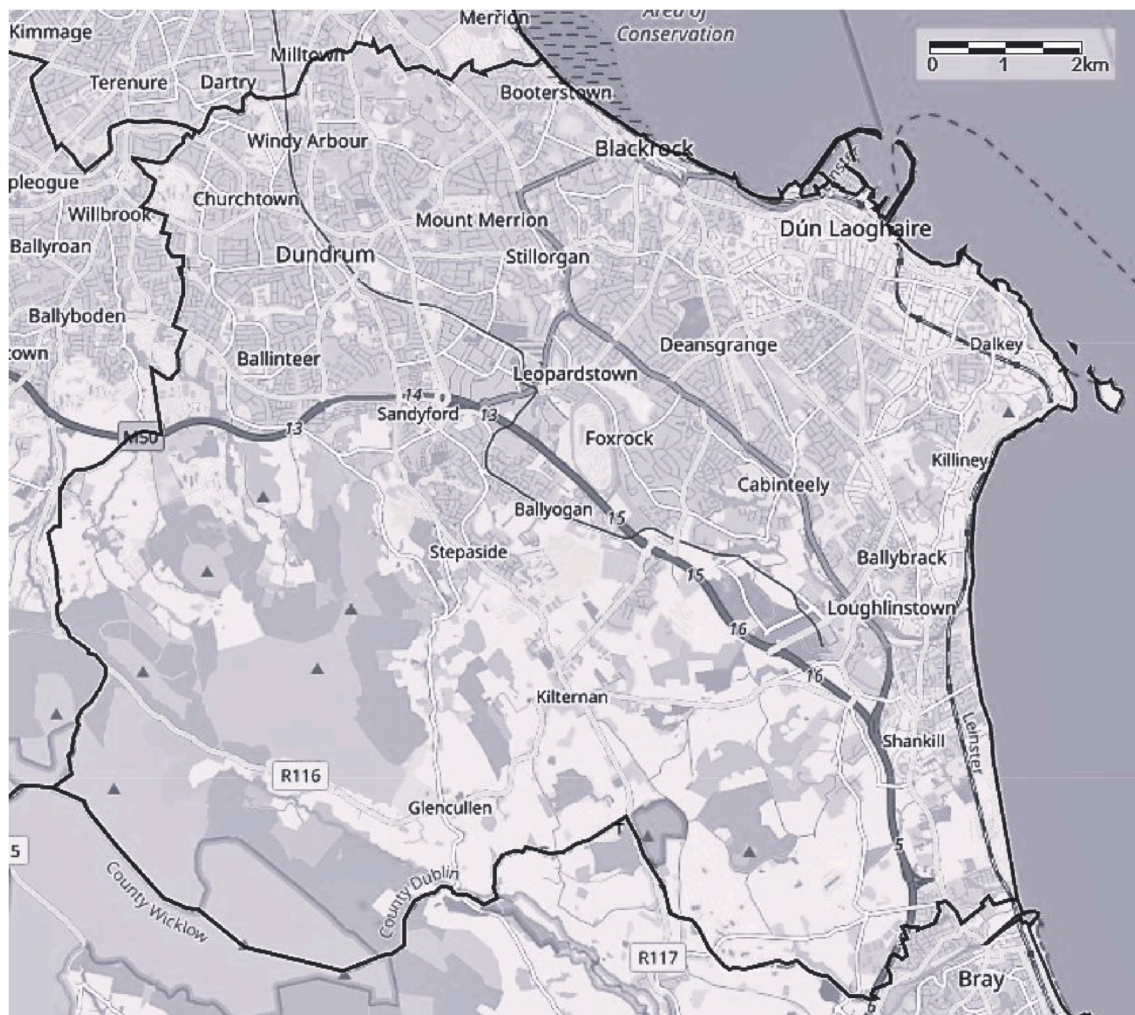


Fig. 1. Dún laoghaire-rathdown county map.

businesses in Dún Laoghaire-Rathdown county to access eCargobikes at a discounted rate for a six month trial period during 2021, thereby providing an opportunity to experimentally substitute delivery and/or service trips currently undertaken by vans or cars with eCargobikes. The GIS tracker data used in this study were gathered from twelve businesses based in Dún Laoghaire-Rathdown county who participated in the trial. These businesses were in the following sectors: food ($n: 7$), flowers ($n: 1$), cycles ($n: 2$), motor parts and accessories ($n: 1$), and regional business promotion ($n: 1$). Customer delivery was the primary purpose for the eCargobike amongst participants followed by service trips (Narayanan and Antoniou, 2022). Three different models of electric cargo cycles were used by participants, each with different cargo capacity and electric ranges: the Raleigh Pro Cargo Bike (80 kg cargo box, 60 km range, $n: 7$), Raleigh Pro Cargo Trike (100 kg cargo box, 70 km range, $n: 1$) and Cube Cargo Hybrid (60 kg cargo box, 60 km range, $n: 4$). All three of these electric cargo cycles had an electric-assist up to a speed of 25 km/h and an approximate charge time of 6 h. Among these participants, the average trip length was 3.34 km while the average trip time was 14 min. No data on trips by other modes were gathered in this study.

3. Intelligent modelling framework for E-cargo bike small business deliveries

An intelligent modelling framework consisting of a) Data Acquisition System, b) Intelligent Learning Unit, and c) Output Unit was constructed for this study. Data was continuously collected in the data acquisition

system. The GIS tracker data from each bike was collected continuously from each of the twelve businesses. These data were supplemented by Met Eireann's (Irish weather service) weather data on rainfall and daily maximum temperature for each trip. This weather data was licenced to the research group. The entire dataset was saved in a secure location, and a base input file was created. This was fed into the learning unit for modelling, and the results obtained are discussed in the following sections. A real-time intelligent learning unit is built and designed specifically for the study. The learning unit's goal is to create a modelling framework that can identify critical variables influencing mode selection, rank them, statistically validate them, and quantify the results in context of this small business e-cargo bike pilot scheme. Mode selection is multifactorial and varies spatially and temporally [26]. As a result, a hybrid modelling framework is built that combines Artificial Intelligence (AI), Statistical, and Mathematical approaches.

3.1. AI approach

The three standard AI approaches are used for modelling, i.e., Deep Learning, Back propagation (BP), and a neural network classifier. Deep learning is a reliable, adaptable, data-driven computing technique replicating diverse processes and accurately capturing nonlinear, complicated, underlying linkages. It is frequently employed in conjunction with the Back Propagation learning technique to address various classification and forecasting issues. Between different neurons belonging to different layers. The input and output are inserted into the

network in the form of neurons belonging to different layers. Through deep learning, two additional layers (hidden layers) are inserted between the two layers of input and output. The primary benefit of this combination is that it imitates the learning process of the human neuron by adjusting the initial connection weights. Based on the size of the error the model predicts, the backpropagation modifies the weights of the connection with the incorrectly categorised output. The learning undergoes continual iteration as part of this adaptive process to enhance their accuracy and precision.

The input data is randomly separated into training (65%), validation (30%), and testing (5%). Bernoulli distribution is used for random division. Two data learning models are constructed representing each of the modelled variables: trip length and weather conditions. Weighted connections, which represent the strength and relationship of the link by a real number, allow neurons from different layers to communicate with one another. Through these weighted connections, the network learns to map the input with the output and carry out higher-order nonlinear mapping that cannot be done using traditional mathematical approaches. Modelling is done by a four-step iterative learning method. Similar to how a signal is conveyed between two brain neurons in a synaptic cleft, a signal is transmitted throughout the network through the developed activation functions. First, random weights are set between the input and hidden layers; the first and second hidden layer, and the hidden and output layer. The Sum of squares error function is used to model the error between the predicted output and the real output. The error is due to the randomly assigned initial weights. The backpropagation method then updates the starting weights considering this modelled error. Every new training epoch updates the weighted connection by adding the most recent weight. This process is iterated using scaled conjugate gradient optimisation (step 1–4).

Step 1: Signal Transmission: For signal transmission between the synaptic cleft activation function, ‘Hyperbolic tangent’ for hidden layers and ‘Identity function’ for the output layers is used.

Step 2: Error modelling: Sum of Squares is used to model the error between the output obtained through modelling and the desired output in the training dataset.

Step 3: Synaptic weight update: The randomly assigned synaptic weights are updated based on the error obtained in previous step. The backpropagation algorithm calculates the gradient of the training error in each training case (epoch); a) Nodes between the input and hidden layers, b) Nodes within the different hidden layers, and c) Nodes between the hidden and output layers. Following the error calculation, the weights are updated in each epoch by adding it to the previously updated weights.

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

To find the critical variables, the data learning method employs a variable importance approach. To compare variables, the normalised significance of each variable to the most critical variable is calculated. This is based upon both the testing and validation datasets. The importance of the independent variable calculates how much the expected output value varies when the input variable changes. Each input variable’s normalised significance is derived by dividing each unique importance value by the most important importance value and expresses the result as a percentage. Table 1 specifically defines the network structure of the AI model. The structure in terms of the topology of the network, training variables and the criterion that is used to stop the iteration and the memory limitations.

Table 2 explicitly defines the AI model layers for modelling trip length, while Table 3 explicitly defines the AI model layers for modelling rainfall conditions. The table explicitly defined the neurons in each layer in terms of the variables modelled, and the number of units in each layer (neurons). The input variables used for each target output are based on

Table 1
Network Structure of the constructed AI-based models.

Function Variable Type	Function Variable	Function Selected/ Value
Network Topology	Activation function between the hidden layers	Hyperbolic Tangent
	Activation function between hidden and output layer	Identity
Training	Learning type	Supervised
	Optimisation method	Gradient Descent (Batch)
	Method of Iteration	Scaled conjugate gradient
	Lambda	0.000001
	Sigma	0.000001
Stopping and Memory Criterion	Centre	0
	Offset	0.000001
	Maximum continuous steps without error deviation	999
	Maximum allocated training time	60
	Maximum epochs allowed in training	999
	Minimum change in training error	0.000001
	Maximum stored cases in modelling memory	0.000001

Table 2
Data Learning model constructed for trip length.

Neuron Layer	Modelled Variable Type	Variable/Values
Input Layer	Input variables	Rainfall Day Max Temp Weekday/ Weekend
	Variables representing the variation in traffic flow conditions	Day of the week Month Hour
Hidden Layer (s)	Total input units	153
	Hidden Layers	2
	First hidden layer units	50
Output Layer	Second hidden layer units	50
	Dependent Variables	Length
	Rescaling Method for Scale Dependents	Standardised
	Error Function	Sum of Squares

Table 3
Data Learning model constructed for rainfall conditions.

Neuron Layer	Modelled Variable Type	Variable/Values
Input Layer	Factors	Month Hour Service launch Trip length Day Max Temp Weekday/Weekend Day of the week Trip time Average speed
		584
Hidden Layers	Total input Units	584
	Hidden Layers	2
	First hidden layer units	50
	Second hidden layer units	50
Output Layer	Activation Function	Hyperbolic tangent
	Dependent Variables	Rainfall
	Rescaling Method for Scale Dependents	Standardised
	Activation Function	Identity
	Error Function	Sum of Squares

the critically identified literature variables. The variation in traffic flow conditions in a particular region can be represented (for mathematical modelling only) by variables, such as trip hour, day, month, or weekday/weekend, and hence have been used as lurking variables for modelling [see27–28].

3.2. Statistical and mathematical modelling

The AI-based modelling must be followed by statistical validation of the determined critical variables. In such cases, the non-parametric technique is the best statistical method, especially when the sample size is small. The two assumptions must be met: a) Randomness of samples and b) Independence of observations [29]. Mode selection is a random phenomenon [30], and, independent of the previous decision to complete the trip on an e-cargo bike, satisfies the two prerequisites. The Chi-square test for goodness of fit, a non-parametric technique explicitly designed to solve such complex nonlinear problems, determines whether a relationship exists between two variables and uses sample data to test the hypothesis regarding the shape of the proportion of population distribution. It assesses how closely sample proportions produced fit the population proportion indicated by the null hypothesis. Each variable in the sample is assigned an n-dimensional frequency distribution matrix. The chi-square test of independence is used to determine whether the observed values deviate significantly from the anticipated values for the cells.

$$\chi^2 = \sum \frac{(O_f - E_f)^2}{E_f}$$

Where O_f = observed value, E_f = expected value

A probability value is computed in addition to the χ^2 statistic. The value of p represents the likelihood that the difference between O_f and E_f , as determined by the χ^2 statistic, is attributable to chance. The frequently accepted value in the literature is $p < 0.05$ [31]. In this case, the observed value differs significantly from the predicted value, implying that the two variables are not independent of one another. The inability to quantify the influence of each variable is a drawback of χ^2 . Pearson proposed the phi ϕ statistic to solve this issue. If the matrix is larger than 2×2 , the Cramer V statistic is applied [32]. It is a post-test used to determine the significance of correlation following the chi-square test.

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

where df is the smaller number of rows and columns.

The output is a single value that needs to be converted into a categorical value using the Cohen's table. It is determined by the degree of freedom as well as the numerical V value [32]. Consider the case of variables with $df = 2$, the following quantification can be inferred depending upon the V value; Small: $0 < V \leq 0.07$, Medium: $0.07 < V \leq 0.21$, and Large: $0.21 < V \leq 0.35$. Similarly, the V value can be calculated for various df 's [33].

4. Results

In this e-cargo bike pilot project, twelve businesses performed 1801 e-cargo bike trips during the trial period of July–November 2021. For these trips, the e-cargo bike was used despite the availability of an alternative mode for each participating small business. Namely, each small business had access to their primary delivery modes prior to the pilot, which chiefly consisted of either an ICE van or car. In the following sections, we model the critical variables influencing trip length (4.1) and e-cargo bike mode choice in wet conditions (4.2). Weather.

4.1. Trip length

The deep learning identified critical variables influencing trip length. These are presented in Table 4 and illustrated in Fig. 2. Identity function is used for activation function. It is a diagonal mapping where inputs are plotted against identical outputs. Target values used to train a model with a linear activation function in the output layer are scaled prior to

Table 4

Importance and normalised importance of input variables in the data learning model for modelling trip length.

Input Variable	I	NI
Weekday/Weekend	0.082	29.20%
Month	0.098	35.00%
Day of the week	0.126	44.90%
Hour	0.197	70.00%
Daily rainfall in mm	0.216	77.10%
Day Max Temp	0.281	100.00%
Total	1.000	

modelling using normalization or standardization transforms. The variable importance approach is employed, that estimates the sensitivity of the model, towards each input variable. The output results values in the range of 0–1, which is an estimate of the sensitivity of the input variable to the model's ability to distinguish between the set-out target variables. The importance of each variable is presented in the form of normalised importance (percentage) that is estimated by dividing the individual importance of the each of the input variables by the importance of most critical input variable. In this case, the most critical variable is the daily maximum temperature, hence its normalised importance is 100%, and the normalised importance of all the other variables are calculated with respect to the daily maximum temperature's importance, and are presented in Table 4. Overall, the model suggests that there is a strong interaction between the weather (temperature and rainfall), and the distance traversed for delivery for an e-cargo bike (i.e., trip length). This is followed by the trip hour and the day of the week that the trip is being undertaken: the spatial variables. The least important variable is whether the trip is made during the week or weekend (i.e., Weekday/Weekend).

Where I = Importance, and NI = Normalised Importance.

The results from deep learning/neural models are sensitive to the combined variable effect. To overcome this limitation, statistical modelling is performed. This also develops confidence in the results, which will help in the application of the results by practitioners. Firstly, the existence of the relationship is confirmed using non-parametric modelling and compared to the deep learning model results. The relationships are then quantified using the standard Cramer's V. Table 5 presents the results of the non-parametric modelling. The statistical non-parametric modelling results indicate that there exists a statistical relationship between the daily maximum temperature, rainfall, hour, and month of the trip, with the trip's length. However, there is no statistical relationship between trip day or whether a trip is performed on a weekday or a weekend. These are the least essential variables determined by the variable importance through deep learning. The statistical quantification of the relationship of each of the input variable in the AI mode with the length of the trip, performed through Cramer's V is presented in Table 6. Each of the relationships Pearson statistic, degree of freedom, and p value is also presented in the corresponding tables.

4.2. Rainfall conditions

Using a neural network classifier, an accurate prediction model is built. Fig. 3 depicts the predicted vs observed values for the variable rainfall conditions. The predicted vs observed line is mostly inclined at a 45° angle, with a few outliers. However, the overall accuracy is significantly high, considering that mode choice is a multifactor variable involving several human factors, demand requests, and other trip-related variables."

The critical variables influencing the decision to travel during wet weather conditions, as identified through the variable importance approach, are presented in Table 7 and illustrated in Fig. 4, with the importance and normalised importance calculated for each of the input variable of the AI model. The most critical variable is the daily maximum temperature, with a normalised importance of 100%. All the other

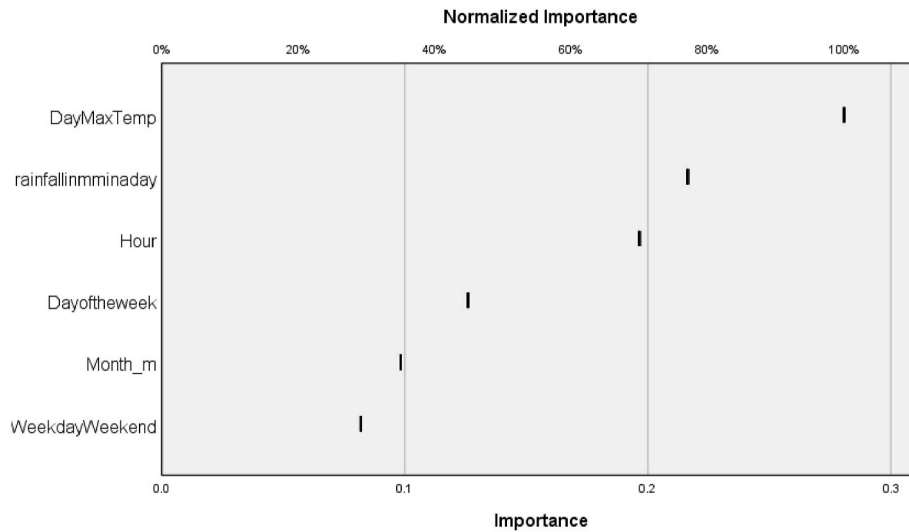


Fig. 2. Graph of the normalised importance of each variable in the trip length predictive data model.

Table 5

Results from non-parametric modelling of the trip length with the input variable of the data learning model.

Variable	Output	Pearson's Statistic	Df	Sig
Weekday/Weekend	Trip length			.125
Month	Trip length	798.2	600	<0.001
Day of the week	Trip length	792.7	720	0.031
Hour	Trip length	3101.5	2280	<0.001
Rainfall	Trip length	5649.5	4320	<0.001
Day maximum temperature	Trip length	14246.2	10,200	<0.001

Table 6

Mathematical quantification of each input variable.

Variable	Output	Cramer's V	Sig	Relation type
Weekday/Weekend	Trip length		.125	n/a
Month	Trip length	.298	<0.001	Medium
Day of the week	Trip length		0.031	n/a
Hour	Trip length	.302	<0.001	Medium
Rainfall	Trip length	.296	<0.001	Medium
Day maximum temperature	Trip length	.306	<0.001	Medium

variables are calculated with respect to the importance of daily maximum temperature. In order of importance, the critical factors influencing users' decision to use an e-cargo bike for delivery during wet weather are: a) Maximum daily temperature, b) Total trip time, c) Months since the service's launch, and d) trip length. The least important variables are the spatial variables of hour, day, month and whether the trip is being performed on the weekday or the weekend (least important variable).

Where I = Importance, and NI = Normalised Importance.

The results from the non-parametric modelling are shown in Table 8,

and the statistical quantification of the relationship is shown in Table 9. Each of the relationships Pearson statistic, Cramer's V, degree of freedom, and p value is also presented in the corresponding tables. The statistical non-parametric modelling results conclude a statistical relationship between all the input variables used in data modelling and weather conditions. There is a powerful association correlation between rainfall and daily maximum temperature. There is a strong correlation between a) trip time, b) months since the service's launch and c) traffic flow conditions (day, month, weekday/weekend). There is a medium association for a) trip length, b) average speed, and c) travel time. These findings validate the results of the deep learning neural model with identical inference.

5. Discussion

5.1. Trip length

It is found that the most critical variable affecting e-cargo bike trip length within this small business pilot programme is daily maximum temperature, followed by rainfall conditions (both of which can be described as 'weather conditions'). This implies that small businesses prefer using e-cargo bikes for deliveries during warmer and drier weather conditions for longer distances. The findings are consistent with the British study [34], that concluded that weather conditions significantly influence bicycle use. A Canadian study [35] based on the perception-based model also reported weather conditions as a strong deterrent to bicycle use. These studies reported results based on user perception rather than mathematically validating their findings against real-world data. A mathematically validated result that colder and wetter weather conditions are a strong deterrent to use of e-cargo bike for goods delivery by small businesses in an Irish context is a unique contribution to the literature. Following weather conditions, the critical variable influencing trip length is the trip hour, representing the flow peak. The daily or monthly variation in traffic flow does not significantly affect the choice of e-cargo bike as a mode of small business goods delivery. The least important variable is whether the trip is made during the week or weekend. Hence it can be concluded that when designing and encouraging the use of e-cargo bikes for small business rental schemes in which an alternative mode of delivery is available (e.g., van or car), the strong influence of local weather conditions compared with spatial variables should be an important consideration in any mode choice modelling.

The results from non-parametric modelling validate the deep learning results. The statistical non-parametric modelling results

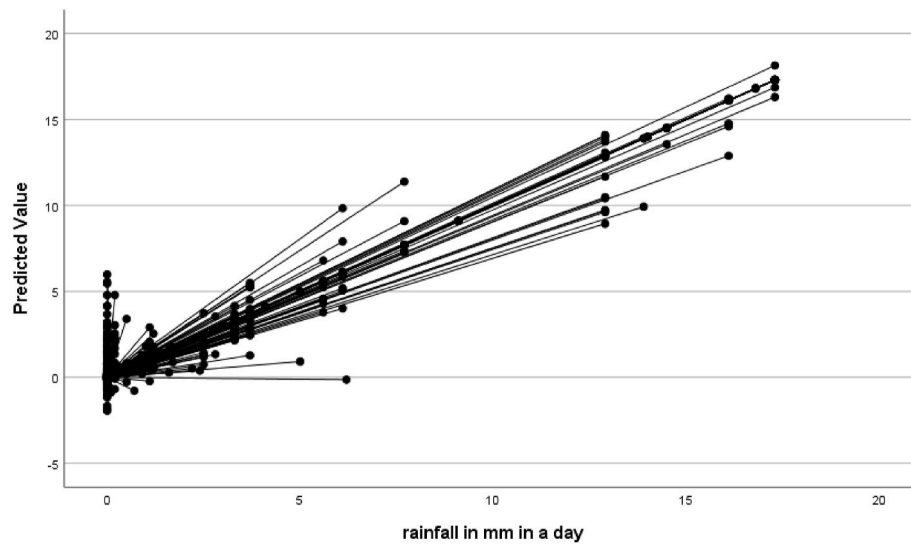


Fig. 3. Predicted vs observed values for the constructed predictive rainfall model.

Table 7

Importance and normalised importance of input variables in the data learning model for modelling rainfall conditions.

Input variables	I	NI
Weekday/Weekend	0.042	12.90%
Month	0.065	19.90%
Day of the week	0.068	21.00%
Hour	0.079	24.50%
Average speed	0.084	25.90%
Length	0.102	31.60%
Service launch	0.108	33.40%
Trip time	0.128	39.50%
Day Max Temp	0.324	100.00%

indicate that a statistical relationship exists between the daily maximum temperature, rainfall, hour, and month of the trip, with trip length. However, no statistical relationship exists between trip day, whether a trip is performed on a weekday or a weekend and trip length. These are the least important variables estimated through the variable importance approach. The results from the Cramer's V modelling demonstrate that all the four statistically significant variables of: a) Daily maximum

temperature, b) Rainfall, c) Trip Hour, and d) Trip Month, have a medium level of association with the chosen trip length. The probability of using an e-cargo bike for goods delivery increases significantly as the daily temperature rises. During dry weather, an e-cargo bike appears to become a more appealing option in the context of this study. Similarly, during non-peak hours, e-cargo bikes appear to become a much more appealing option for small business deliveries. This could be attributed to a variety of factors not accounted for in this study, such as potentially easier and faster use of road spaces as an e-cargo bike rider during non-peak hours due to less motor-vehicle traffic. As e-cargo bikes are much larger vehicles than standard e-bikes, during peak hours, they may not be as suitable for filtering through motor-vehicle traffic congestion or riding within (currently available) segregated cycle spaces as standard e-bikes, as indicated in the study of Blazejewski et al. [36]. Furthermore, an e-cargo bike delivery rider may be more sensitive to other environmental conditions than delivery drivers, particularly weather conditions for longer trips – as this study suggests. A small business may be more likely to perform a delivery trip on an e-cargo bike for a shorter trip; however, as the trip length increases, the influence of weather conditions become more significant in mode choice. The results demonstrate that a small business is more likely to select an e-cargo bike as a delivery mode for a longer trip when weather conditions are drier and warmer.

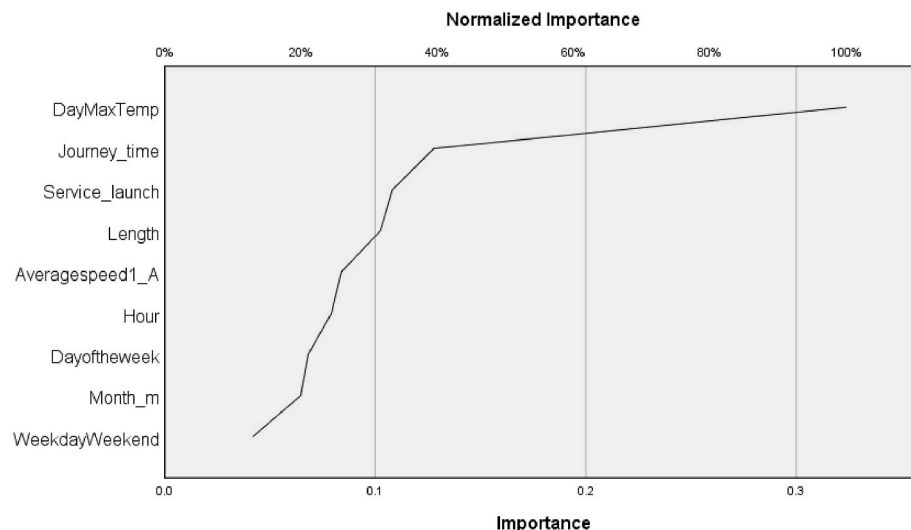


Fig. 4. Normalised importance of input variables in the data learning model for modelling rainfall conditions.

Table 8

Results from non-parametric modelling of rainfall with the input variable of the data learning model.

Variable	Output	Pearson Chi-Square Statistic	df	p-value
Weekday/Weekend	Rainfall in mm	460.7	36	<0.001
Month	Rainfall in mm	2054.8	180	<0.001
Day of the week	Rainfall in mm	2735.1	216	<0.001
Hour	Rainfall in mm	1327.4	684	<0.001
Average Speed	Rainfall in mm	6631.5	5112	<0.001
Length of trip	Rainfall in mm	5649.5	4320	<0.001
Service Launch	Rainfall in mm	2054.8	180	<0.001
Trip time	Rainfall in mm	14,089	13,752	<0.001
Daily maximum temperature	Rainfall in mm	37385.3	3060	<0.001

Table 9

Mathematical quantification of each input variable.

Variable	Output	Cramer's V	p-value	Relation type
Weekday/Weekend	Rainfall in mm	0.507	<0.001	Strong
Month	Rainfall in mm	.476	<0.001	Strong
Day of the week	Rainfall in mm	.504	<0.001	Strong
Hour	Rainfall in mm	.197	<0.001	Medium
Average Speed	Rainfall in mm	.321	<0.001	Medium
Length of trip	Rainfall in mm	.296	<0.001	Medium
Service Launch	Rainfall in mm	.476	<0.001	Strong
Trip time	Rainfall in mm	.467	<0.001	Strong
Daily maximum temperature	Rainfall in mm	.761	<0.001	Very Strong

Explanations for this phenomenon in the context of this pilot scheme are not accounted for in this study. However, one possibility is that during wet weather conditions, wet road surfaces may increase the likelihood of losing traction while riding a (loaded) e-cargo bike – particularly for inexperienced riders – thereby deterring from the choice of this mode. Contact with the drain covers during wet weather conditions could also lead to a less safe cycling environment [see37]. Furthermore, e-cargo bike riders with an alternative delivery mode may be poorly equipped for riding in wet and/or cold weather (e.g., keeping themselves and their goods dry and warm) due to a lack of experience using this delivery mode in varying conditions and a lack of access to insulating and waterproofing materials. It is widely reported and acknowledged in the literature that a single bad experience in cycling mode can cause the user to hesitate and even switch modes [38], although e-cargo bikes for small business logistics in particular do not appear to have been explored in this respect.

5.2. Rainfall conditions

The most critical variable affecting the selection of e-cargo bike during wet weather conditions is daily maximum temperature, thereby suggesting that there is a combined effect of these two weather

variables. These variables are followed by the variables of total trip time, time since the launch of the service, and trip length. Consequently, it can also be calculated that even if the weather changes from dry to wet, an e-cargo bike is still an appealing mode for small business deliveries in the context of the study if the temperature of the day is not low, and vice versa. The deterring effect of wet weather on e-cargo bike use for small business deliveries is exacerbated by a drop in temperature. However the mode remains appealing even if weather conditions are wet when the expected trip time is short. The attractiveness of the mode gets further compounded as the trip time increases. Trip length is the fourth critical variable. The length and time of the trip are covariates; however, it has been discovered that the trip time is a more critical variable than the length of the trip in relation to rainfall conditions. The results validate various generalised cost models for mode choice (see Ref. [39]), indicating that travel time is a more significant impediment than travel distance. Another critical variable is the time since the service has been launched. As these schemes are still in their infancy, the potential users and small business owners are likely inexperienced in operating e-cargo bikes for deliveries and in incorporating their use into their everyday business logistics operations. This context-specific study suggests that as small businesses become more familiar with the e-cargo bike as a potential mode of goods delivery, they may use it more; this is promising in light of the potential for major market penetration of e-cargo bikes and e-bikes as goods delivery mode alternatives to cars and vans in urban areas [9,12]. Schemes that enable e-cargo bike access may necessitate an initial government push/subsidisation [36], particularly in light of the potential costs of e-cargo bike use relative to cars and vans – especially for larger logistics operations [40–42]. As e-cargo bikes may become integrated into small business logistics operations and, more broadly, a city's transportation system, other groups may begin to consider e-cargo bikes as a viable alternative to cars and vans for making cargo journeys. The promotion of e-cargo bike subsidy schemes can provide an important enabler for the adoption of e-cargo bikes because they allow people to trial these vehicles before renting them at full price or purchasing them as a cargo vehicle.

The results from both the models (trip length and rainfall conditions) clearly demonstrates that both the variables of wet weather and temperature are the critical variables most affecting the decision of small businesses to select an e-cargo bike for the delivery of their goods. It can be concluded that there is a strong joint effect of rainfall and temperature, that affects the attractiveness of an e-cargo bike as a mode of small business goods delivery. This joint effect could be considered in e-cargo bike mode choice modelling in future small business e-cargo bike promotion schemes. Due to the insulation and protection from weather conditions that motor-vehicle transport provides, it is unlikely that such an effect is as prevalent for car and van deliveries. On this basis, these findings could inform broader measures to promote e-cargo bike use within – for example – mobility-as-a-service schemes. Namely, measures could be taken that disincentivise the choice of car and van use in dry and warm weather (i.e., when e-cargo bike use appears to be more appealing) conditions and incentivise e-cargo bike use in wet and cold weather (i.e., when e-cargo bike use appears to be less appealing). However, other potential measures might be relevant, such as improving the insulation from cold and protection from wet conditions for both e-cargo bike riders and their goods; the study of Blazejewski et al. [36], for example, remarks on how loss of warmth for hot foot deliveries was a barrier to e-cargo bike use by small businesses. Furthermore, research examining bike-sharing in Ireland has also highlighted the significance of weather conditions on bike-sharing usage, reporting shorter trips in wetter conditions [43]. Importantly, similar to public bike-share usage, reduced cycling in wetter and colder conditions in the context of this study – where alternative modes were available for delivery – could perhaps be additionally explained by cultural factors regarding what is 'normal' and 'practical' transport in particular weather conditions. This perspective has been convincingly argued by Hudde [44], who demonstrates that variations in cycling rates between the Netherlands –

which has relatively stable year-round cycling rates – and Germany – which demonstrates much greater seasonal variation – is not explained by variations in seasonal weather conditions. Accordingly, measures to change dominant cultural beliefs around cycling as a predominantly ‘fair weather’ activity that is impractical in wet and cold conditions could be another important area for intervention, including with e-cargo bikes.

Further research should develop new mode and route choice modelling theories explicitly designed for small business e-cargo bike deliveries and consider their revealed preferences within varied weather, traffic flow, and infrastructural conditions. A hybrid methodology involving artificial intelligence and mathematical modelling, as demonstrated in this study, would be helpful in such modelling.

6. Conclusion

E-cargo bikes are receiving growing interest as vehicle for moving goods more sustainably in and through urban areas [3] and there have been a considerable number of cargo bike trials across Europe promoting their integration into logistics operations [4]. This study models e-cargo bike use for the delivery of goods by small businesses and provides insight into the impact of different trip lengths and weather conditions on e-cargo bike selection. Based on an e-cargo bike trial with small businesses in Dún Laoghaire-Rathdown, Ireland, this study designed a new intelligent learning system that explicitly combines artificial intelligence and mathematical approaches for e-cargo bikes.

An intelligent modelling framework consisting of a) Data Acquisition System, b) Intelligent Learning Unit, and c) Output Unit was constructed. The learning unit identifies, ranks, statistically validates, and quantifies critical variables influencing mode selection. The twelve businesses that took part in the study made 1801 trips between July and November 2021. The daily maximum temperature is found to be the most critical variable influencing trip length, followed by the prevalent rainfall conditions and flow peak. Small business users prefer e-cargo bikes for goods delivery over longer distances and in warmer and drier weather. For a shorter trip, a small business may be inclined to perform delivery by e-cargo bike; however, as the trip length increases, environmental factors such as weather and traffic flow conditions influence mode choice. The following important factors influence the decision of small business to use an e-cargo bike for cargo delivery during wet weather: a) Maximum daily temperature, b) Total trip time, c) Months since the service’s launch and d) trip length. The effect of wet weather is exacerbated by a drop in temperature, making e-cargo bikes less appealing as a delivery mode for small businesses. As travel time increases, the mode’s attractiveness decreases significantly. In the context of this study, it has been discovered that trip time is a more critical variable than trip length in relation to rainfall conditions. The study clearly demonstrates that there is a strong joint effect of rainfall conditions and temperature on e-cargo bike mode choice by small businesses which could be considered in e-cargo bike mode choice modelling in future small business e-cargo bike promotion schemes. More broadly, these results support measures to enable riders to use e-cargo bikes in all weather conditions, including by tackling potential cultural beliefs regarding the appropriate weather conditions for cycling [44].

As an alternative to traditional generalised cost modelling, integrated mode and route choice modelling for a e-cargo riders may be beneficial for transportation practitioners, as demonstrated by the study. Namely, this study has exemplified the benefits of a hybrid methodological framework that could be applied to various e-cargo bike schemes being trialled in different parts of the world. In this way, the model developed in this study could contribute to greater adoption of e-cargo bikes in last-mile urban logistics, thereby contributing to the decarbonisation of the transport logistics sector.

Credit author statement

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Validation, Formal analysis, Investigation, Resources, Writing – original draft, Writing – review & editing, Visualization. Robert Egan: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization. Conor Mark Dowling: Conceptualization, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Project administration, Funding acquisition. Brian Caulfield: Conceptualization, Methodology, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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References

- [1] Gruber J, Narayanan S. Travel time differences between cargo cycles and cars in commercial transport operations. *Transport Res Rec* 2019;2673(8):623–37.
- [2] Cox P, Rzewnicki R. Cargo bikes: distributing consumer goods. In: Cox P, editor. *Cycling cultures*. Chester: University of Chester Press; 2015. p. 130.
- [3] European Commission. Communication from the commission to the European parliament, the Council, the European economic and social committee and the committee of the regions. The New EU Urban Mobility Framework 2022. https://transport.ec.europa.eu/system/files/2021-12/com_2021_811_the-new-eu-urban-mobility.pdf. [Accessed 17 June 2022].
- [4] European Commission. Mobility and transport: 6.2 cycle logistics. n.d. https://transport.ec.europa.eu/transport-themes/clean-transport-urban-transport/cycling/guidance-cycling-projects-eu/cycling-measures/62-cycle-logistics_en. [Accessed 17 June 2022].
- [5] Cycling Industries Europe. Cie expert group on cargo bikes and cycle logistics. Cycling Industries Europe; 2021. <https://cyclingindustries.com/what-we-do/expert-groups/cargo-bike-cycle-logistics>. [Accessed 17 June 2022].
- [6] Geels FW. A socio-technical analysis of low-carbon transitions: introducing the multi-level perspective into transport studies. *J Transport Geogr* 2012;24:471–82.
- [7] Dún Laoghaire-Rathdown County Council. Local business: cargo bike pilot scheme aims to get businesses on their bikes. 2021. <https://www.dlrccoco.ie/en/news/general-news-press-releases/cargo-bike-pilot-scheme-aims-get-businesses-their-bikes>. [Accessed 17 June 2022].
- [8] Narayanan S, Antoniou C. Electric cargo cycles—a comprehensive review. *Transport Pol* 2022;116:278–303.
- [9] Llorca C, Moekel R. Assessment of the potential of cargo bikes and electrification for last-mile parcel delivery by means of simulation of urban freight flows. *European Transport Research Review* 2021;13(1):1–4.
- [10] Melo S, Baptista P. Evaluating the impacts of using cargo cycles on urban logistics: integrating traffic, environmental and operational boundaries. *European transport research review* 2017;9(2). 1–0.
- [11] Dalla Chiara G, Alho AR, Cheng C, Ben-Akiva M, Cheah L. Exploring benefits of cargo-cycles versus trucks for urban parcel delivery under different demand scenarios. *Transport Res Rec* 2020;2674(5):553–62.
- [12] Gruber J, Kihm A, Lenz B. A new vehicle for urban freight? An ex-ante evaluation of electric cargo bikes in courier services. *Research in Transportation Business & Management* 2014;11:53–62.
- [13] Lenz B, Riehle E. Bikes for urban freight?: experience in Europe. *Transport Res Rec* 2013;2379(1):39–45.
- [14] Giordano A, Matthews HS, Baptista P, Fischbeck P. Impacts of topography and weather barriers on commercial cargo bicycle energy using urban delivery crowdsourced cycling data. *Sustain Cities Soc* 2022;76:103326.
- [15] Rudolph C, Gruber J. Cargo cycles in commercial transport: potentials, constraints, and recommendations. *Research in Transportation Business & Management* 2017; 24:26–36.

- [16] Schliwa G, Armitage R, Aziz S, Evans J, Rhoades J. Sustainable city logistics—making cargo cycles viable for urban freight transport. *Research in Transportation Business & Management* 2015;15:50–7.
- [17] Thoma L, Gruber J. Drivers and barriers for the adoption of cargo cycles: an exploratory factor analysis. *Transport Res Procedia* 2020;46:197–203.
- [18] Gruber J, Kihm A. Reject or embrace? Messengers and electric cargo bikes. *Transport Res Procedia* 2016;12:900–10.
- [19] Narayanan S, Gruber J, Liedtke G, Antoniou C. Purchase intention and actual purchase of cargo cycles: influencing factors and policy insights. *Transport Res Pol Pract* 2020;155:31–45.
- [20] Central Statistics Office. National travel survey 2019. 2020. <https://www.cso.ie/en/releasesandpublications/ep/p-nts/nationaltravelsurvey2019/>. [Accessed 17 June 2022].
- [21] Conway R, Morrow J, Brennan R, Mulvey C, ÓhAiseadha C. The current state of cycling infrastructure in Dublin and Copenhagen; a comparison of cycling infrastructure in 8 radial routes into the city centre of Dublin and Copenhagen. *Ir Med J* 2019;(1):112.
- [22] Dublin City Council & National Transport Authority. Enabling the city to return to work: interim intervention mobility programme for Dublin city. 2020. <https://www.dublincity.ie/sites/default/files/2020-12/dublin-city-covid-mobility-programme-tagged.pdf>. [Accessed 15 June 2022].
- [23] Dún Laoghaire-Rathdown County Council. Coastal mobility interventions. 2020. <https://www.dlrcoco.ie/en/transportation-infrastructure/coastal-mobility-interventions>. [Accessed 5 July 2022].
- [24] Technical University Dublin. DLR covid-19 mobility review. 2021. <https://www.tudublin.ie/media/website/news/2021/main-news/TU-Dublin-DLR-COV-ID-19-Mobility-Review-FINAL-RESIZED.pdf>. [Accessed 1 June 2022].
- [25] Dún Laoghaire-Rathdown County Council. DLR connector: pre-design consultation. 2021. <https://www.dlrcoco.ie/en/news/public-consultation/dlr-connector-pre-design-consultation>. [Accessed 20 June 2022].
- [26] De Vos J. The shifting role of attitudes in travel behaviour research. *Transport Rev* 2022;1–7.
- [27] Malik FA, Dala L, Busawon K. Intelligent nanoscopic cyclist crash modelling for variable environmental conditions. *IEEE Trans Intell Transport Syst* 2021.
- [28] Malik FA, Dala L, Busawon K. Deep neural network-based hybrid modelling for development of the cyclist infrastructure safety model. *Neural Comput Appl* 2021; 33(18):11603–16.
- [29] Pallant J. Survival manual. A step by step guide to data analysis using SPSS 2011:4.
- [30] Li X, Tang J, Hu X, Wang W. Assessing intercity multimodal choice behavior in a touristy city: a factor analysis. *J Transport Geogr* 2020;86:102776.
- [31] Field A. Discovering statistics using IBM SPSS statistics. sage; 2013.
- [32] Cohen J. Statistical power analysis for the behavioral sciences. Routledge; 2013.
- [33] Akoglu H. User's guide to correlation coefficients Turkish Journal of Emergency Medicine. Emergency Medicine Association of Turkey 2018.
- [34] Gatersleben B, Appleton KM. Contemplating cycling to work: attitudes and perceptions in different stages of change. *Transport Res Pol Pract* 2007;41(4): 302–12.
- [35] Winters M, Davidson G, Kao D, Teschke K. Motivators and deterrents of bicycling: comparing influences on decisions to ride. *Transportation* 2011;38(1):153–68.
- [36] Blazejewski L, Sherriff G, Davies N. Delivering the last mile : scoping the potential for E-cargo bikes. 2020. <https://usir.salford.ac.uk/id/eprint/59007/8/Delivering%20the%20Last%20Mile%20-%20Blazejewski%20et%20al%202020.pdf>. [Accessed 15 January 2023].
- [37] Zhou B, Zhao W, Guo W, Li L, Zhang D, Mao Q, Li Q. Smartphone-based road manhole cover detection and classification. *Autom ConStruct* 2022;140:104344.
- [38] Ogilvie D, Egan M, Hamilton V, Petticrew M. Promoting walking and cycling as an alternative to using cars: systematic review. *Bmj* 2004;329(7469):763.
- [39] Ha J, Lee S, Ko J. Unraveling the impact of travel time, cost, and transit burdens on commute mode choice for different income and age groups. *Transport Res Pol Pract* 2020;141:147–66.
- [40] Choubassi C, Seedah DPK, Jiang N, Walton CM. Economic analysis of cargo cycles for urban mail delivery. *Transport Res Rec* 2016;2547(1):102–10.
- [41] Robichet A, Nierat P, Combes F. First and last miles by cargo bikes: ecological commitment or economically feasible? The case of a parcel service company in paris. *Transport Res Rec* 2022. 03611981221086632.
- [42] Sheth M, Butrina P, Goodchild A, McCormack E. Measuring delivery route cost trade-offs between electric-assist cargo bicycles and delivery trucks in dense urban areas. *European transport research review* 2019;11(1):1–2.
- [43] Caulfield B, O'Mahony M, Brazil W, Weldon P. Examining usage patterns of a bike-sharing scheme in a medium sized city. *Transport Res Pol Pract* 2017;100:152–61.
- [44] Hudde A. It's the mobility culture, stupid! Winter conditions strongly reduce bicycle usage in German cities, but not in Dutch ones. *J Transport Geogr* 2023;106: 103503.