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Appearance and behaviour: Are cyclist physical attributes reflective of their preferences and habits?

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ABSTRACT

Cyclist physical attributes are important for performance aspects such as speed, effort, and energy expenditure, and could also be systematically related to preferences and behaviour. Casual assumptions (stereotypes) about cyclists based on their appearance are common among road users but largely untested. This study examines whether readily observable physical attributes are significantly associated with cycling efficiency, preferences, and habits for a sample of 531 intercepted cyclists in Vancouver, Canada. Due to strong correlations among physical attributes, a typology is developed using cluster analysis based on physical aspects of the bicycle (bicycle type, tire type, tire width, tire pressure, and cargo) and rider (apparel and riding position). Results show that Mountain, Hybrid and Road type cyclists are, in that order, systematically more efficient, more comfortable on major roads, cycle more consistently year-round, cycle faster, and engage in more vigorous physical activity. Still, the hypothesis of significant relationships between appearance and behaviour is only weakly supported: behaviour differences among cyclist types are modest and wide ranges of preferences and behaviours within the physical clusters could be viewed as a refutation of common cyclist stereotypes. For application of the physical typology, readily observable attributes such as tire type can be used as indicators to infer resistance parameters and more generally characterize a sample of cyclists. This study establishes associations, not causality, and future work should examine a potential positive feedback effect between equipment efficiency and cycling frequency.

1. Introduction

Cycling in urban environments has been fostered by many cities around the world, with goals such as reducing congestion and pollution emissions and increasing physical activity (Pucher et al., 2011; Pucher and Buehler, 2012; Su et al., 2010). As urban cycling grows, there is an accompanying need to develop more sophisticated bicycle travel modelling tools, including behavioural, safety, health, and operations models. Better understanding and representation of bicycle travelers can improve models and contribute to the design of more targeted cycling policies, which has motivated development of several cyclist typologies (Damant-Sirois and El-Geneidy, 2015; Dill and McNeil, 2013; Gatersleben and Haddad, 2010; Piatkowski and Marshall, 2015; Winters et al., 2011).

To date, cyclist physical attributes have been largely excluded from bicycle transportation analysis, limiting consideration of important aspects of physical performance including speed, power, energy expenditure, and breathing rates (Bigazzi and Figliozzi, 2015; Tengattini and Bigazzi, 2017). Physical performance is important for outcomes such as health and safety, and can also affect travel behaviour through influences on route and mode choices. For example, cyclist avoidance of hills is likely related to the excess energy and time required to ascend them, and decisions about whether to cycle are related to the perceived physical effort required.

Physical characterization of cyclists can include several types of attributes, some readily observable (bicycle type, clothing, riding position) and others more difficult to measure (resistance parameters). Bicycle resistance forces are important determinants of required pedaling effort and commonly parameterized as the coefficient of rolling resistance C_r (unit-less), and the effective frontal area $A_f C_d$ (m^2) (Bigazzi and Figliozzi, 2015). Mass m (kg) of the cyclist, bicycle, and cargo also directly influence required pedaling effort. Various other physical attributes of the cyclist and bicycle are related to resistance parameters and so can indirectly affect pedaling effort, such as tire pressure and width, riding position, and cyclist body size and shape (Burke, 2003; Wilson and Papadopoulos, 2004). These other physical attributes are often easier to determine for a sample of cyclists than the resistance parameters, which require more invasive measurement

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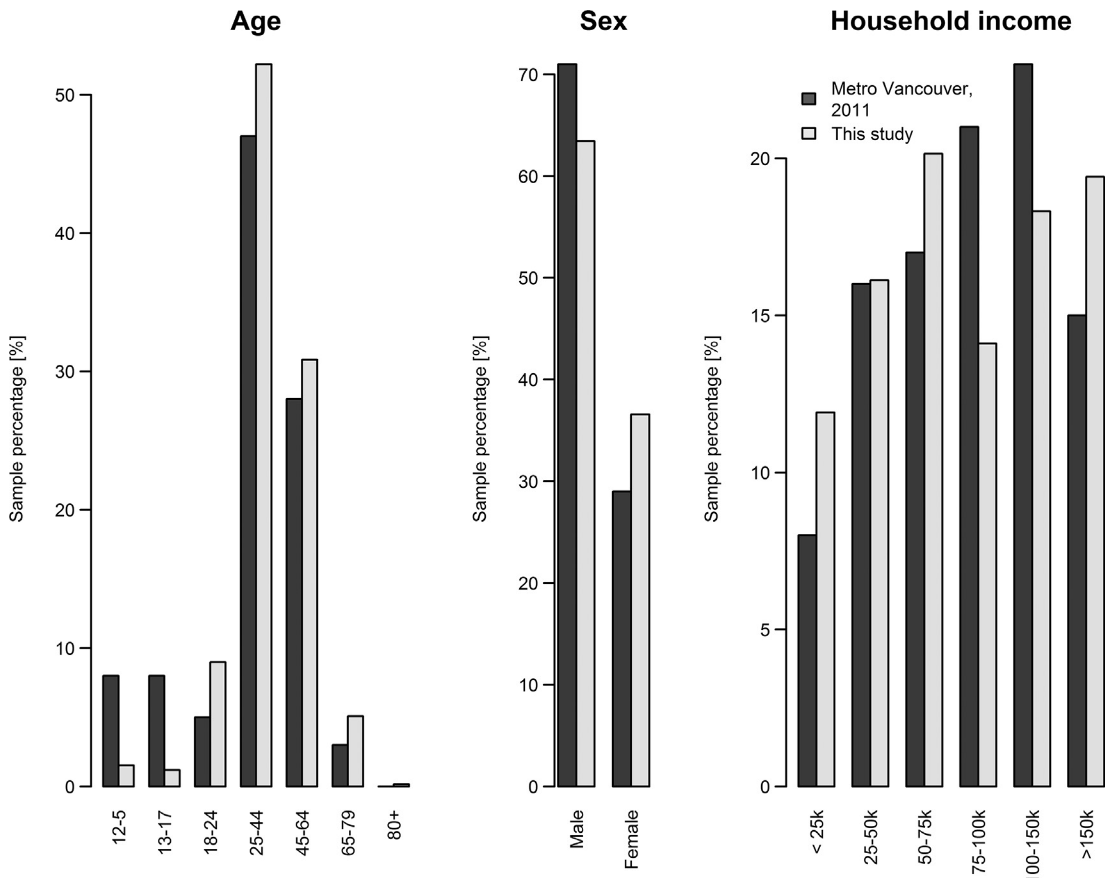

Fig. 1. Comparison of sample with cyclists in a 2011 regional household travel survey (TransLink, 2013).

methods than simple observation.

The extent to which cyclist preferences and habits are systematically related to their physical attributes is still unknown. Observable and unobservable physical attributes could influence behaviour through cycling efficiency, and conversely also be manifestations of cyclist identity and preferences, which also influence behaviour. Casual and largely untested assumptions (stereotypes) about cyclists based on their appearance are common among road users, such as cyclists with more "sporty" gear being more confident on their bicycles and on higher-traffic routes. In previous research, cyclist appearance has been described as a barrier to wider acceptance of cycling, a reflection of cyclist identity, and a mechanism for normalizing urban cycling (Aldred, 2013; Aldred and Jungnickel, 2014; Daley and Rissel, 2011; Fishman et al., 2012; Gatersleben and Haddad, 2010; Goodman et al., 2014).

The objective of this paper is to examine whether readily observable physical attributes of cyclists are systematically related to their cycling efficiency, preferences, and habits. Due to strong correlations among physical attributes, a physical typology is developed using cluster analysis, based on data from an intercept survey of urban cyclists in Vancouver, Canada. Relationships are then examined between cyclist physical types and (1) cycling efficiency, as represented by resistance parameters; (2) cyclist preferences, such as comfort on different types of roadway facilities; and (3) travel habits, such as self-reported cycling frequency and seasonality. The physical types are also compared to the well-known preference-based "four types of cyclists", originally developed by Roger Geller in Portland, Oregon (Geller, 2009). The two main goals of this research are to test the hypothesis that cyclist appearance is systematically related to non-physical attributes such as preferences and habits, and to determine whether readily observable physical attributes such as bicycle type can be used as an indicator to more generally characterize a sample of cyclists.

2. Method

A cyclist intercept survey was conducted in Vancouver, Canada at 9 locations over 18 days in summer 2016. Locations were selected to sample from a variety of contexts (university, residential, downtown, waterfront path). Passing cyclists were recruited with signs placed within one block of the survey location. Participating cyclists (648 in total) first completed a questionnaire with socio-demographic, current trip, cycling preference, and general travel behaviour questions. Simultaneously, cyclist and bicycle physical attributes were measured, including masses, cargo, and tire pressure, type, and width. Participants then completed a coast-down test, which involved coasting from a cruising speed to a stop over approximately 100 m of paved bikeway, from which resistance parameters were determined. Details of the coast-down test method are given in Tengattini and Bigazzi (2018a). The estimated resistance parameters (rolling resistance, C_r, and effective frontal area, $A_f C_d$) represent the first- and third-order effects of speed on power.

Cluster analysis was applied to develop a physical typology using only observed physical attributes directly assessed by the researchers during the survey. Estimated resistance parameters and questionnaire responses were excluded to create a typology that is easy to apply and based on readily observable attributes. Categorical variables were bicycle type (Road, Hybrid, Mountain, Cruiser, or Other, based primarily on frame geometry and handlebar type); tire type (Slick, Commuter, or Knobby, with decreasing smoothness); cyclist apparel (Sport or Casual); and riding position (Drops, Hoods, or Tops, decreasingly aerodynamic). Bicycle, tire, apparel, and position classifications were designated and aligned by the researchers before the survey using example photos of cyclists. Numeric variables were tire pressure, tire width, and number of cargo pieces.

Cluster analysis was performed using the statistical software R with the "cluster" and "fcp" packages (Hennig, 2015; Maechler et al., 2016). Because both continuous and categorical variables were included, a meaningful dissimilarity matrix could not be computed using a classic Euclidean metric. Instead, a Gower metric (Gower, 1971) was used, and k-medoid clustering was performed. Maximization of the mean of average silhouette width for growing k was used to identify the optimum number of clusters (Reynolds et al., 2006).

Resistances parameters (C_r, $A_f C_d$, and m), cycling preferences, and travel habits, which were not used to generate the clusters, were examined for systematic relationships with the clusters (i.e. cyclists physical types). Non-parametric Kolgoromov-Smirnov (K-S) tests and chi-squared (χ^2) tests were used to identify statistically significant differences among the clusters at $p < 0.05$ for continuous and categorical variables, respectively.

3. Results

Fig. 1 gives age, sex, and income information for the sample, with a comparison to cyclists in a Vancouver metropolitan area 2011 household travel survey (TransLink, 2013). The sample socio-demographics are generally representative of the regional cycling population, with fewer youth under 18, more females, and several bi-directional differences in income categories.

3.1. Physical typology

Of 648 total participants, resistance parameters were successfully estimated for 557 (91 coast-down test results were discarded, mainly due to poor fit) – see Tengattini and Bigazzi (2018b). An additional 26 participants were removed due to other missing data (measurements or questionnaire responses), leaving 531 observations for the cluster analysis. Fig. 2 shows cluster analysis results as participant membership in three identified clusters along the first two principal components. Cluster sizes are 133, 270, and 128 for clusters 1, 2, and 3, respectively.

To attach physical meaning to each cluster, Figs. 3–5 show differences by cluster of the seven physical attributes used to identify clusters. K-S and χ^2 tests are used to identify significant differences in attribute distributions between clusters at $p < 0.05$. All attributes are significantly different among all three clusters with the exception of cyclist apparel, which is not significant between clusters 1 and 2, and number of cargo pieces, which is not significantly different among any clusters. Tire type is the most distinct characteristic of the clusters, followed by bicycle type and other tire characteristics (width and pressure); the other three factoring variables (clothing, cargo, and position) are less distinct among clusters. Hence, the clusters are primarily identified by the bicycle itself, and secondarily by the rider and cargo.

Based on their attributes, clusters 1, 2, and 3 are named Mountain (M), Hybrid (H), and Road (R) cyclist types. Cluster M is composed of more than half mountain bicycles ridden in the tops position with knobby, wide, and low-pressure tires. Cluster R is predominantly road bicycles with slick, narrow, high-pressure tires. Cluster H, as the name implies, lies between the other two clusters on almost all attributes.

Table 1 gives continuous and ordinal socio-demographic and household variables by cluster. M members had significantly lower household income than the other two clusters and H members were significantly older than R members based on K-S tests at $p < 0.05$. In addition, M members had significantly lower levels of education at a lesser significance level ($p < 0.10$). Physical typology relationships with day and location of sampling were investigated, and all insignificant ($p \geqslant 0.10$). Differences in self-reported sex and measured body mass among physical typologies were also insignificant ($p \geqslant 0.40$).

3.2. Relationships with resistance parameters

Fig. 6 shows distributions of resistance parameters and equipment (bicycle + cargo) mass by cyclist physical type (cluster) using boxplots. Table 2 gives mean and standard deviation of resistance parameters and equipment mass by type. Power and energy required to cycle a given distance and speed will increase with all three factors, and all three are significantly higher for M as compared to R cyclist types. As with the attribute comparisons above, H cyclists are between the R and M cyclist types. H cyclists are similar to R cyclists in terms of rolling resistance (likely related to tire characteristics), but similar to M cyclists in terms of drag resistance (likely related to riding position) and mass. Based on their resistance attributes, M, H, and R cyclists, in that order, have increasingly efficient equipment, as expected.

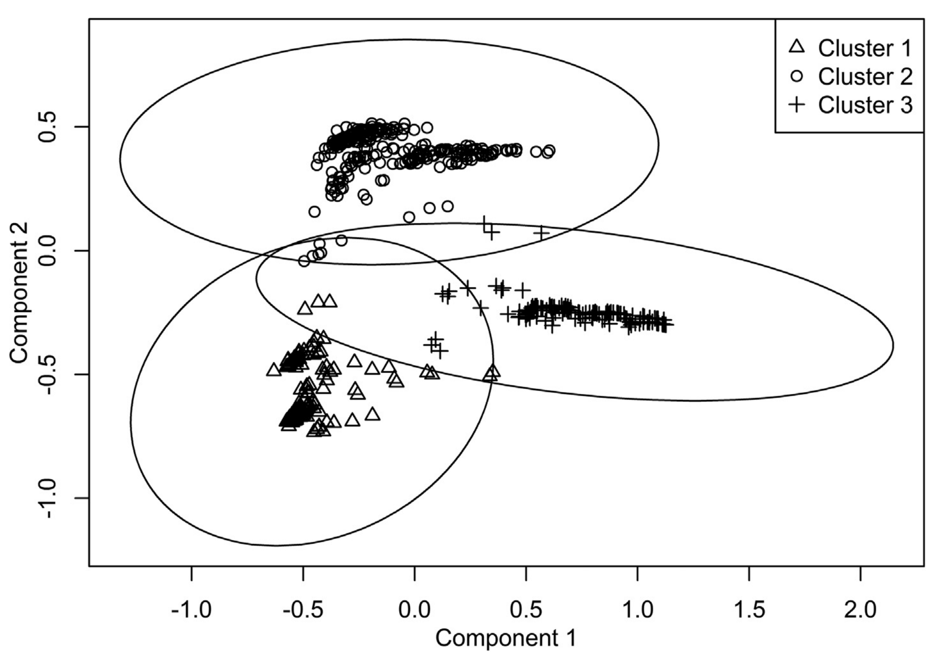

Fig. 2. Participants classified in three clusters along the first two principal components.

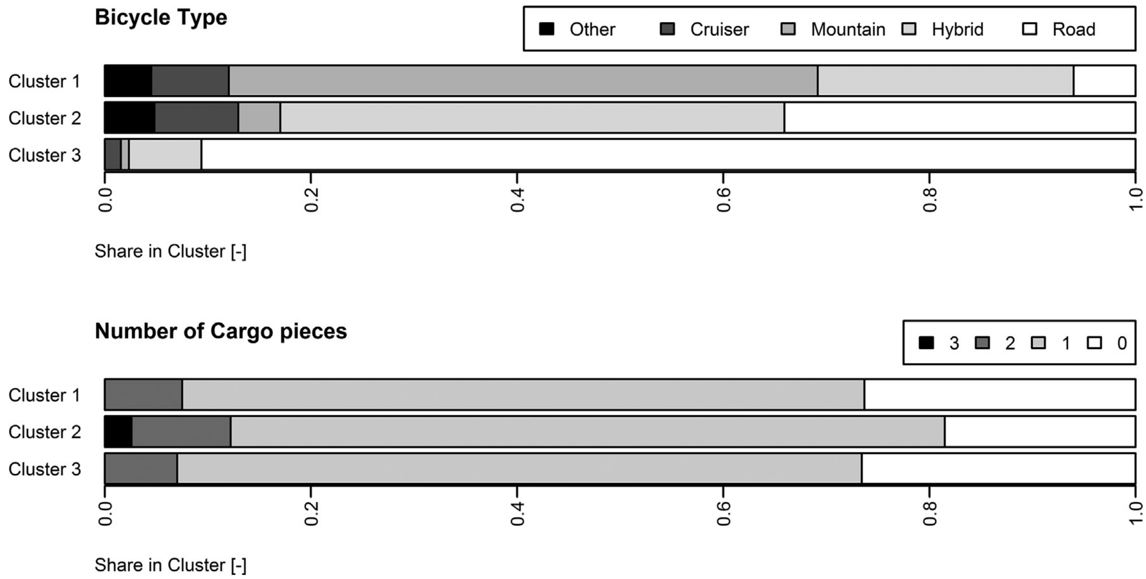

Fig. 3. Bicycle type and cargo by cluster.

3.3. Relationships with cycling preferences and perceptions

Table 3 gives mean and standard deviation of preference and perception responses by cyclist physical type. All three types of cyclists are more comfortable on facilities with increased separation from motor vehicles, as expected (Caulfield et al., 2012; Rupi and Schweizer, 2018; Sanders, 2016; Winters and Teschke, 2010). In addition, R cyclists report the highest comfort levels on all facilities, particularly on major streets where the differences in comfort between R and M cyclists are significant for all three types of separation from traffic. Other differences in reported comfort are not significant, but the relationships are consistent. Comfort levels on low-traffic streets and off-street paths are the most consistent across typologies. Differences in self-reported comfort levels among physical types could be due to numerous factors, including cycling frequency and experience, exposure to mixed-traffic riding, trip purpose, and typical cycling speed.

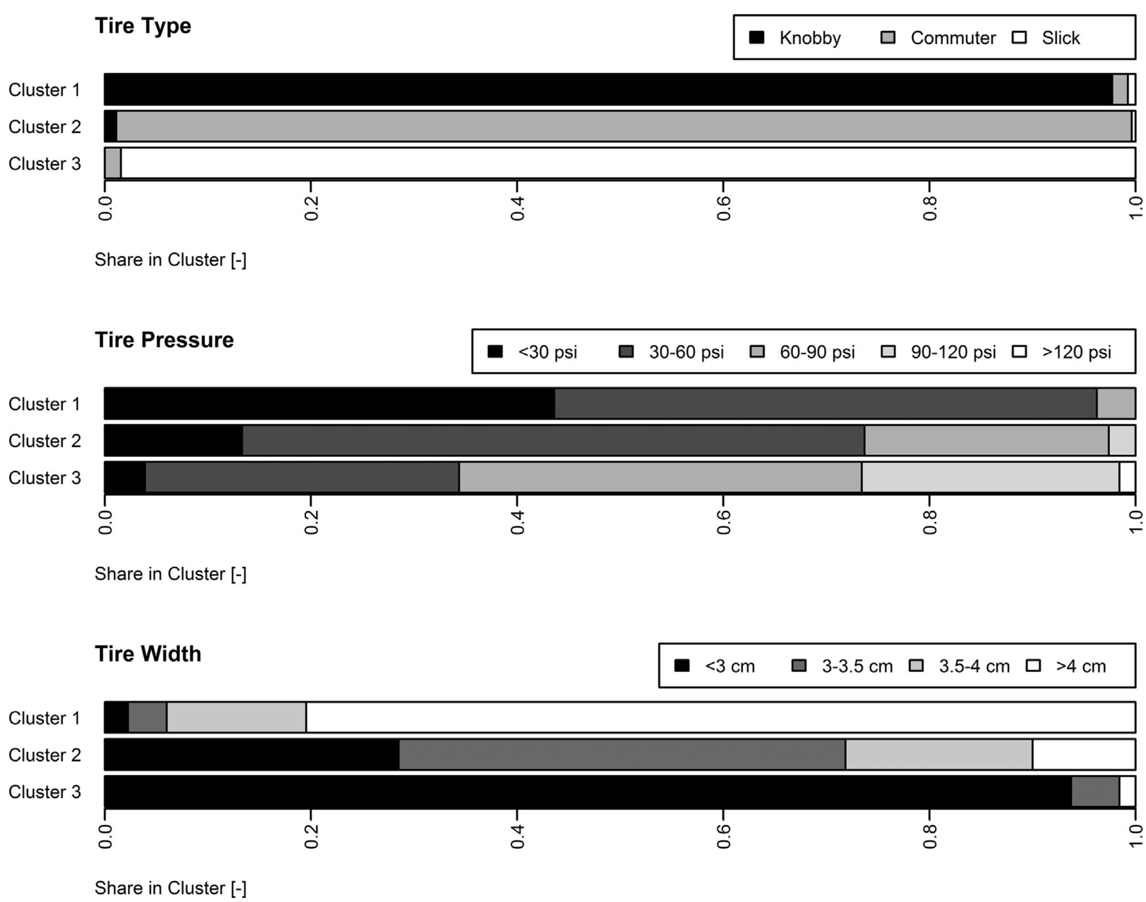

Fig. 4. Tire attributes by cluster.

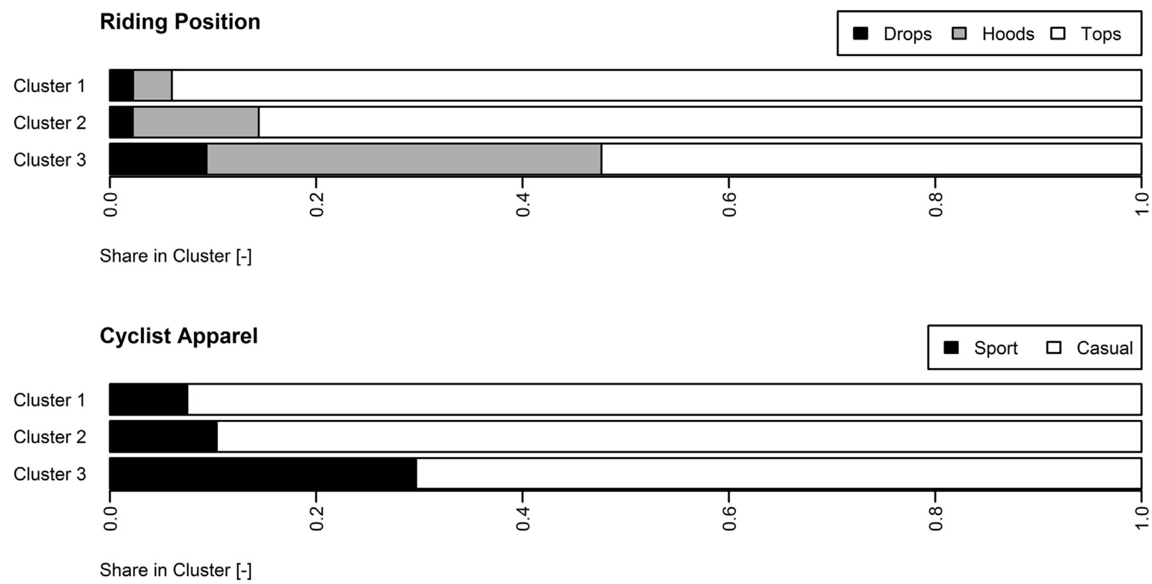

Fig. 5. Cyclist attributes by cluster.

Table 1
Mean (standard deviation) of socio-demographic and household variables by cluster.[1]

	R	H	M
Age (years)	37.25 (12.63)	41.00^{R} (14.95)	38.65 (15.63)
Household income (CAD)	92,415 (51,039)	93,879 (54,182)	$78,491^{R,H}$ (57,063)
Household size (persons)	2.34 (1.08)	2.49 (1.31)	2.57 (1.31)
Motorized vehicles in household	2.03 (0.77)	2.12 (0.87)	2.07 (0.91)
Level of education[2]	3.78 (0.91)	3.84 (1.10)	3.48 (1.27)

[1] superscripts indicate comparison clusters for which significant differences were found (K-S test, $p < 0.05$).

[2] ordinal variable from 1-"high school or less" to 5-"master's or doctorate degree".

Self-reported maintenance condition of the bicycle was slightly lower for M cyclists than R or H cyclists ($p = 0.09$ and 0.06, respectively), which could relate to the higher measured resistance shown above. M, H, and R type cyclists, in that order, increasingly agree that they 1) would like to cycle more than they do now, 2) consider cycling to be a form of exercise, and 3) enjoy physical activity – although the differences are not significant. These results suggest that the physical typology relates to perceptions of and enthusiasm for cycling as a physical activity, in addition to relating to resistance characteristics.

Fig. 7 shows cluster composition by the preference-based "four types of cyclists" typology (Geller, 2009). Classification as "no way, no how", "interested but concerned", "confident and enthused", or "strong and fearless" was based on the method in Dill and McNeil (2013), including questionnaire responses about comfort levels on different facility types, interest in cycling more often, and cycling frequency. The three physical types follow a M < H < R pattern of increasing proportions in the "confident and enthused" and "strong and fearless" categories, which is consistent with the results in Table 3. The distributions are significantly different between R and M cyclists (χ^2 test, $p < 0.05$).

3.4 Relationships with travel habits

Table 4 gives mean and standard deviation of self-reported travel habits by cyclist physical type. None of the travel frequency differences by type are significant at $p < 0.05$, with the exception of less frequent car-share usage by M than R cyclists. The R type cycled the most, particularly for utilitarian purposes (commuting and shopping), but the M type reported more recreational cycling trips, and there was large within-cluster variation in the self-reported cycling frequency. Most of the sample reported cycling and walking at least "several times a week", which is consistent with the self-reported cycling frequency by purpose. R types used private vehicles slightly more often, while M types used transit slightly more often.

M, H, and R type cyclists, in that order, had increasingly high self-reported cycling speeds and agreed more with the statement that they cycle "year-round, regardless of the weather". In both cases the M and R differences were significant. R cyclists also had significantly higher self-reported weekly vigorous physical activity than the other two types. Self-reported trip distance and travel time for the intercepted trip were not significantly different among cyclist types. Purpose for the intercepted trip also was not significantly different by type, although R cyclists had the highest share of commuters whereas M cyclists had the highest share on recreational trips, consistent with the self-reported cycling frequency results.

4. Discussion and conclusion

Overall, the central hypothesis tested in this research was weakly supported: cyclist physical attributes are systematically related to their preferences and habits, but the differences are modest and in many cases not statistically significant. The developed physical typology is significantly related to several of the preference and behaviour measures, and there are consistent and logical patterns among M, H, and R-type cyclists in socio-demographics, resistance parameters, preferences, and habits. Still, the results indicate a wide range of preferences and behaviours within the physical clusters, and the lack of large differences among M, H, and R type cyclists could be viewed as a refutation of common cyclist stereotypes.

Resistance parameters are significantly lower for R than H and M cyclists, as expected from the physical attributes used to define the typology such as tire type and riding position (Wilson and Papadopoulos, 2004). The resistance differences could also be related to

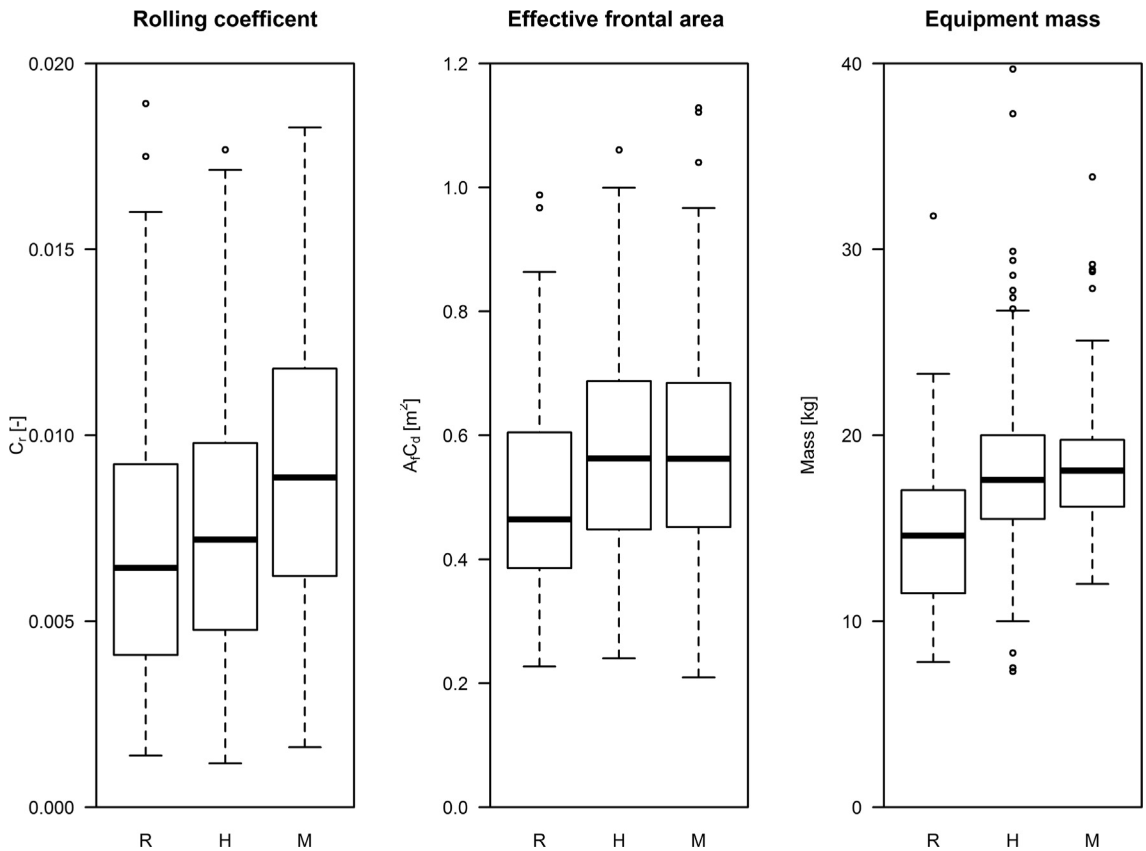

Fig. 6. Distributions of rolling coefficient, effective frontal area, and equipment mass by cyclist type (central line gives the median, box gives the IQR, whiskers give the range up to 1,5 * IQR, and circles are observations outside the whisker range).

Table 2
Mean (standard deviation) of resistance parameters and equipment mass by type.[1]

	R	H	M
C_r [–]	0.0069 (0.0035)	0.0074 (0.0034)	0.0092^{R,H} (0.0039)
$A_f C_d$ [m^2]	0.495 (0.148)	0.577^R (0.171)	0.579^R (0.178)
Bicycle + Cargo mass [kg]	14.6 (4.1)	18.5^R (6.2)	18.4^R (3.5)

[1] superscripts indicate comparison types for which significant differences were found (K-S test, $p < 0.05$).

Table 3
Mean (standard deviation) of preferences and perceptions by type.[1]

		R	H	M
Comfort[2] on	Off street path away from motor vehicles	3.90 (0.31)	3.89 (0.39)	3.80 (0.51)
	Local street with low traffic and speeds	3.80 (0.40)	3.65 (0.58)	3.70 (0.48)
	Major street with physical separation	3.57 (0.68)	3.46 (0.68)	3.39^R (0.71)
	Major street with painted separation	3.29 (0.69)	3.03 (0.79)	2.94^R (0.81)
	Major street without separation	2.43 (0.95)	2.11^R (1.02)	2.06^R (0.91)
Self-reported bicycle maintenance condition[3]		3.02 (0.89)	3.02 (0.75)	2.80 (0.81)
I would like to travel by bicycle more than I do now[4]		3.87 (1.11)	3.78 (1.12)	3.67 (1.23)
Bicycling is a form of exercise for me[4]		4.63 (0.75)	4.56 (0.8)	4.33 (1.07)
I enjoy physical activity[4]		4.75 (0.60)	4.68 (0.71)	4.54 (0.99)

[1] Superscripts indicate comparison types for which significant differences were found (K-S tests, $p < 0.05$).
[2] ordinal variable from 1-"very uncomfortable" to 4-"very comfortable".
[3] ordinal variable from 1-"poor" to 4-"excellent".
[4] ordinal variable from 1-"strongly disagree" to 5-"strongly agree".

bicycle maintenance condition, which was lowest for M cyclists. The systematic differences in resistance parameters have direct implications for power and energy modelling, with further potential impacts on speed, ventilation, route, safety, and health (Bigazzi and Figliozzi, 2015; Mueller et al., 2015; Olds, 2001; Parkin and Rotheram, 2010; Tengattini and Bigazzi, 2017). For application, the physical clusters were strong, so physical classification can be made based on only a few observed attributes – particularly tire type. For example, cyclists could be classified from video data, and the developed typology used to infer representative resistance parameters and other attributes. The typology could also be applied to joint simulation of physical and behavioural attributes of cyclists in detailed bicycle travel models.

M, H, and R cyclists, in that order, increasingly perceive cycling as exercise, ride faster, and enjoy and engage in physical activity. In the same order, cyclists are increasingly comfortable on all facilities, particularly those less separated from motor vehicle traffic. These findings suggest systematic speed and route choice differences by physical type. Furthermore, the cyclist types likely have different health effects from engaging in urban cycling, with implications for exercise, pollution, and safety dimensions of health impact assessments. These differences also have equity implications because the least-efficient M cyclists are significantly lower-income, likely related to purchase cost differences among bicycle types.

M, H and R cyclists, in that order, increasingly cycle year-round and

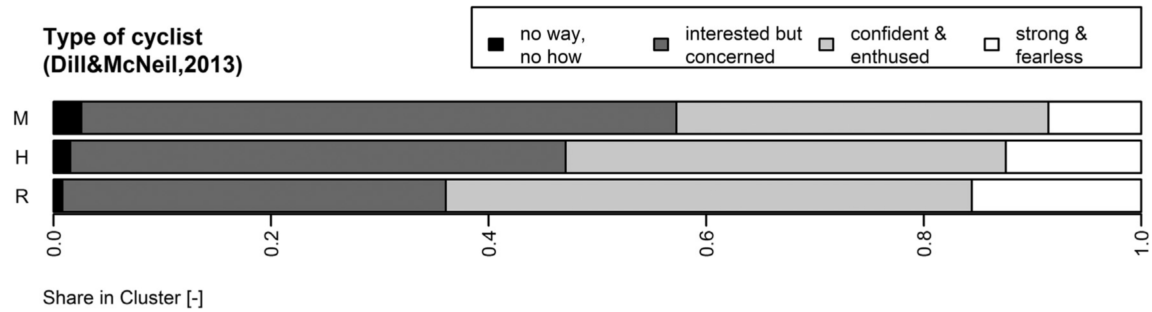

Fig. 7. Cluster composition according to the preference-based "four types of cyclists"

Table 4
Mean (standard deviation) of travel habits by cyclist type.[1]

		R	H	M
Mode usage (any purpose)[2]	Private vehicle (driver or passenger)	2.88 (1.21)	2.73 (1.36)	2.71 (1.45)
	Car-share vehicle (driver or passenger)	1.68 (0.87)	1.56 (0.90)	1.39[R] (0.75)
	Taxi	1.42 (0.62)	1.41 (0.68)	1.37 (0.64)
	Public transit	2.56 (1.03)	2.68 (1.11)	2.93 (1.23)
	Bicycle	4.56 (0.73)	4.34 (1.06)	4.23 (1.01)
	Walk	4.16 (1.10)	4.26 (1.13)	4.07 (1.26)
Cycling by purpose [number of the last 30 days]	Days with commuting trips	14.50 (10.35)	13.79 (10.84)	12.48 (10.67)
	Days with shopping trips	11.12 (8.55)	10.51 (8.86)	10.17 (9.72)
	Days with recreational trips	10.18 (8.66)	8.83 (8.50)	11.15 (9.47)
Other habits	I bicycle year-round, regardless of the weather[3]	3.94 (1.32)	3.72 (1.42)	3.42[R] (1.45)
	Typical self-reported speed[4]	2.56 (0.57)	2.18[R] (0.61)	2.10[R] (0.68)
	Moderate physical activity [hrs/wk]	4.86 (1.87)	4.63 (1.91)	4.70 (1.90)
	Vigorous physical activity [hrs/wk]	4.27 (2.00)	3.24[R] (2.15)	3.27[R] (2.22)
	Equivalent physical activity [hrs/wk][5]	12.46 (2.69)	11.15[R] (3.15)	11.16[R] (3.29)

[1] superscripts indicate comparison types for which significant difference were found (K-S tests, $p < 0.05$).
[2] ordinal variable from 1-"almost never" to 5-"almost daily".
[3] ordinal variable from 1-"strongly disagree" to 4-"strongly agree".
[4] ordinal variable from 1-"slower than most cyclists" to 3-"faster than most cyclists".
[5] computed as (moderate physical activity) + 2*(vigorous physical activity).

for utilitarian purposes, although overall (summer) cycling frequency was not significantly different by cluster. Differences in auto and transit mode usage were also not significant, but suggest more substitution of private auto by R cyclists and of transit by M cyclists. The preference results suggest that provision of more protected facilities would have a stronger effect on cycling comfort and appeal for less-efficient and slower (M) cyclists. The habit results further suggest potential differences in mode substitution and utilitarian cycling frequency, related to the physical typology. Consistent with the preference patterns, the physical types significantly relate to the preference-based "four types of cyclists" typology, with higher proportions of M cyclists classified as "interested but concerned" and R cyclists as "confident and enthused" and "strong and fearless". This sample of cyclists has a higher proportion of "confident" and "fearless" respondents than past research on the general population (Dill and McNeil, 2016, 2013), as would be expected. The M cyclists are most like the general population in terms of distribution of preference types.

A key uncertainty is the direction of causality. M, H, and R cyclists have increasing efficiency benefits, with systematically lower resistances (energetic efficiency), higher speeds (time efficiency), and comfort on a wider range of facilities (route choice efficiency), all of which could make cycling more attractive. This study identifies associations, but it is unknown the extent to which a cyclist's equipment efficiency affects riding preferences and habits, and vice versa. Previous research suggested leisure cycling can increase commute cycling and vice versa (Kroesen and Handy, 2014; Park et al., 2011), and some physical attributes can reflect evolving cyclist identity (Aldred, 2013; Aldred and Jungnickel, 2014). For cycling efficiency, there could be a positive feedback loop, mediated by social identity, in which more efficient equipment fosters more cycling and increased comfort, further motivating and justifying investment in improved equipment as the cyclist becomes more experienced. Examination of this hypothesis is left for future research incorporating information about cycling experience and cycling expenditures.

Policy implications include the potential effects on behaviour of educating novice cyclists about bicycle efficiency, including maintenance and equipment selection. In addition, policies aiming to reduce bicycle theft could be important for fleet efficiency if risk of theft is a factor in decisions about purchasing more efficient road-style bicycles. M and R type cyclists might be differently motivated to cycle by different facility types, as discussed above, and by different marketing strategies (R cyclists perceive it more as an exercise activity). The modest differences in comfort levels among cyclist types suggest that more separated bicycle facilities provide benefits for all types of cyclists – even "sporty" cyclists.

This study has several limitations. The preference and habit data from the questionnaire are self-reported and subject to response biases, particularly social desirability bias, hence the reported amount of cycling and physical activity could be inflated. Unless the bias were different by type, however, this would not significantly affect the findings. The data collection was conducted in the summer and some responses were likely affected by the favorable summer cycling weather in Vancouver – particularly the questions about cycling frequency in the previous 30 days. The sample would likely shift toward the R type (with more self-reported year-round cyclists) if repeated in winter, and perhaps yield greater differences in cycling frequency by type.

Transferability is also unknown; the sample is broadly representative of regional cyclists in terms of age, sex, and income, but due to the intercept recruitment method could be biased toward avid and leisurely cyclists (potentially off-setting attributes if sport and commuter cyclists are more avid than leisure cyclists). The sample might not represent cyclists in other cities, particularly those with substantially different bicycle fleets. Cycling equipment is potentially similar in cities around the U.S. and Canada, but bicycles and cycling behaviour are expected to vary more on other continents. Previous research found consistent cycling preference patterns in U.S. cities (Dill and McNeil, 2016), and further research is needed to evaluate the transferability of the physical typology.

In future research, a longitudinal survey could be used to explore the hypothesis of a cyclist development process that manifests as a physical and behavioural typology shift over time. In addition, the causality direction could be examined by testing whether improved equipment and maintenance precedes or follows preference and behaviour shifts. The factors relating mode substitution to cyclist type should be further explored, particularly alternative usage of private cars and transit with mediating effects of income. Finally, future research could explore the utility of physical typologies in cyclist travel models, including speed, route, and mode choice models.

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References

Aldred, R., 2013. Incompetent or too competent? Negotiating everyday cycling identities in a motor dominated society. Mobilities 8, 252–271. http://dx.doi.org/10.1080/17450101.2012.696342.
Aldred, R., Jungnickel, K., 2014. Why culture matters for transport policy: the case of cycling in the UK. J. Transp. Geogr. 34, 78–87. http://dx.doi.org/10.1016/j.jtrangeo.2013.11.004.
Bigazzi, A.Y., Figliozzi, M.A., 2015. Dynamic ventilation and power output of urban bicyclists. Transp. Res. Rec.: J. Transp. Res. Board 2520, 52–60. http://dx.doi.org/10.3141/2520-07.
Burke, E., 2003. High-tech Cycling. Human Kinetics.
Caulfield, B., Brick, E., McCarthy, O.T., 2012. Determining bicycle infrastructure preferences – A case study of Dublin. Transp. Res. Part D: Transp. Environ. 17, 413–417. http://dx.doi.org/10.1016/j.trd.2012.04.001.
Daley, M., Rissel, C., 2011. Perspectives and images of cycling as a barrier or facilitator of cycling. Transp. Policy 18, 211–216. http://dx.doi.org/10.1016/j.tranpol.2010.08.004.
Damant-Sirois, G., El-Geneidy, A.M., 2015. Who cycles more? Determining cycling frequency through a segmentation approach in Montreal, Canada. Transp. Res. Part A: Policy Practice 77, 113–125. http://dx.doi.org/10.1016/j.tra.2015.03.028.
Dill, J., McNeil, N., 2016. Revisiting the Four Types of Cyclists. Transp. Res. Rec.: J. Transp. Res. Board 2587, 90–99. http://dx.doi.org/10.3141/2587-11.
Dill, J., McNeil, N., 2013. Four types of cyclists? Transp. Res. Rec.: J. Transp. Res. Board 2387, 129–138. http://dx.doi.org/10.3141/2387-15.
Fishman, E., Washington, S., Haworth, N., 2012. Barriers and facilitators to public bicycle scheme use: a qualitative approach. Transp. Res. Part F: Traffic Psychol. Behav. 15, 686–698. http://dx.doi.org/10.1016/j.trf.2012.08.002.
Gatersleben, B., Haddad, H., 2010. Who is the typical bicyclist? Transp. Res. Part F: Traffic Psychol. Behav. 13, 41–48. http://dx.doi.org/10.1016/j.trf.2009.10.003.
Geller, R., 2009. Four types of cyclists. Portland Office of Transportation, Portland, Oregon.
Goodman, A., Green, J., Woodcock, J., 2014. The role of bicycle sharing systems in normalising the image of cycling: an observational study of London cyclists. J. Transp. Health 1, 5–8. http://dx.doi.org/10.1016/j.jth.2013.07.001.
Gower, J.C., 1971. A general coefficient of similarity and some of its properties. Biometrics 27, 857–871. http://dx.doi.org/10.2307/2528823.
Hennig, C., 2015. fpc: Flexible Procedures for Clustering.
Kroesen, M., Handy, S., 2014. The relation between bicycle commuting and non-work cycling: results from a mobility panel. Transportation 41, 507–527. http://dx.doi.org/10.1007/s11116-013-9491-4.
Maechler, M., Rousseeuw, P., Struyf, A., Hubert, M., Hornik, K., 2016. cluster: Cluster Analysis Basics and Extensions.
Mueller, N., Rojas-Rueda, D., Cole-Hunter, T., de Nazelle, A., Dons, E., Gerike, R., Götschi, T., Int Panis, L., Kahlmeier, S., Nieuwenhuijsen, M., 2015. Health impact assessment of active transportation: a systematic review. Prev. Med. 76, 103–114. http://dx.doi.org/10.1016/j.ypmed.2015.04.010.
Olds, T.S., 2001. Modelling human locomotion: applications to cycling. Sports Med. 31, 497–509.
Park, H., Lee, Y.J., Shin, H.C., Sohn, K., 2011. Analyzing the time frame for the transition from leisure-cyclist to commuter-cyclist. Transportation 38, 305–319. http://dx.doi.org/10.1007/s11116-010-9299-4.
Parkin, J., Rotheram, J., 2010. Design speeds and acceleration characteristics of bicycle traffic for use in planning, design and appraisal. Transp. Policy 17, 335–341. http://dx.doi.org/10.1016/j.tranpol.2010.03.001.
Piatkowski, D.P., Marshall, W.E., 2015. Not all prospective bicyclists are created equal: The role of attitudes, socio-demographics, and the built environment in bicycle commuting. Travel Behav. Soc. 2, 166–173. http://dx.doi.org/10.1016/j.tbs.2015.02.001.
Pucher, J., Buehler, R., Seinen, M., 2011. Bicycling renaissance in North America? An update and re-appraisal of cycling trends and policies. Transp. Res. Part A: Policy Practice 45, 451–475. http://dx.doi.org/10.1016/j.tra.2011.03.001.
Pucher, J.R., Buehler, R., 2012. City Cycling. MIT Press, Cambridge, MA, USA.
Reynolds, A.P., Richards, G., de la Iglesia, B., Rayward-Smith, V.J., 2006. Clustering rules: a comparison of partitioning and hierarchical clustering algorithms. J. Math. Model Algor. 5, 475–504. http://dx.doi.org/10.1007/s10852-005-9022-1.
Rupi, F., Schweizer, J., 2018. Evaluating cyclist patterns using GPS data from smartphones. IET Intel. Transport Syst. 12, 279–285. http://dx.doi.org/10.1049/iet-its.2017.0285.
Sanders, R.L., 2016. We can all get along: the alignment of driver and bicyclist roadway design preferences in the San Francisco Bay Area. Transp. Res. Part A: Policy Practice 91, 120–133. http://dx.doi.org/10.1016/j.tra.2016.06.002.
Su, J.G., Winters, M., Nunes, M., Brauer, M., 2010. Designing a route planner to facilitate and promote cycling in Metro Vancouver, Canada. Transp. Res. Part A: Policy Practice 44, 495–505. http://dx.doi.org/10.1016/j.tra.2010.03.015.
Tengattini, S., Bigazzi, A., 2018a. Validation of an outdoor coast-down test to measure bicycle resistance parameters. J. Transp. Eng., Part A: Syst. 144, 04018031. http://dx.doi.org/10.1061/JTEPBS.0000152.
Tengattini, S., Bigazzi, A.Y., 2018b. Physical characteristics and resistance parameters of typical urban cyclists. J. Sports Sci. 1–9. http://dx.doi.org/10.1080/02640414.2018.1458587.
Tengattini, S., Bigazzi, A.Y., 2017. Context-sensitive, first-principles approach to bicycle speed estimation. IET Intel. Transport Syst. 11, 411–416. http://dx.doi.org/10.1049/iet-its.2017.0012.
TransLink, 2013. 2011 Metro Vancouver Regional Trip Diary - Analysis Report.
Wilson, D.G., Papadopoulos, J., 2004. Bicycling Science. MIT Press.
Winters, M., Davidson, G., Kao, D., Teschke, K., 2011. Motivators and deterrents of bicycling: comparing influences on decisions to ride. Transportation 38, 153–168. http://dx.doi.org/10.1007/s11116-010-9284-y.
Winters, M., Teschke, K., 2010. Route preferences among adults in the near market for bicycling: findings of the cycling in cities study. Am. J. Health Promotion 25, 40–47. http://dx.doi.org/10.4278/ajhp.081006-QUAN-236.