Energy Expenditure in Cycling: A Behavioral Approach to Route Choice Modeling

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Motivation and Research Gaps

As cities worldwide shift toward sustainable transportation, cycling stands out as a key solution for future urban transportation systems. Understanding route preferences is essential to designing accessible and attractive cycling networks. Toward that end, route choice modelling is a powerful tool to analyze observed behavior and develop valuable insights for planning user-oriented cycling infrastructure. A growing body of research focuses on utilitarian cycling behavior, particularly how it is affected by network factors such as infrastructure type.

Bicycle route attractiveness and selection have been extensively studied through choice models, with examples spanning recent studies [1], [2] and earlier fundamental research [3], [4]. However, accurately modeling cyclist route choice behavior remains a challenge, particularly in understanding the role of energy expenditure. Energy expenditure is a defining aspect for cyclists: 73% state that they "consider energy expenditure (physical effort) when choosing a bicycle route" [5]. Yet, its precise influence on route decisions remains unquantified and underexplored. Existing studies often examine energy expenditure as an outcome rather than a motivator of route choices [6], [7], and while cyclist preferences to avoid energy expenditure are frequently assumed [8], [9], [10], this assumption lacks explicit quantification or empirical validation to date. The relationship is complicated by the observation that the desire for at least some amount of exercise is a common motivator of the choice to cycle [11], [12], and some studies report preferences for non-zero gradients, particularly for men [13], [14].

The relationship between energy expenditure and route choice is further nuanced by the fact that cyclists often have varying motivations, capacities, and interests. While some seek to minimize physical effort, others cycle for exercise, leading to preferences for routes with non-zero gradients or greater challenges [15], [16], [17]. This diversity in preferences underscores the need to account for behavioral heterogeneity in cyclist route choice models [10], [18]. Understanding and addressing these variations is crucial for accurate modeling. It is also essential for promoting equitable cycling networks that adapt to the needs of diverse groups, including transportation-disadvantaged [19].

Speed is another complicating factor, as it mediates the relationship between route factors (e.g., distance and hills) and fundamental costs for cyclists (e.g., time and energy) [20], [21]. Furthermore, speed is itself related to the network (grade, surface, facility type), contextual (temperature, wind, trip purpose), and cyclist (gender, age, bicycle type) factors that can affect route preferences [22], [23], [24]. Current modeling practice neglects the role of speed as a mediator of cyclist preferences, often reducing it to a static average value [4], [25].

To summarize, although the importance of energy expenditure for cyclists is widely acknowledged, it is rarely quantified and has not been integrated into utilitarian cycling analyses. We assume that energy expenditure underlies at least some preferences regarding energy-related route factors (hills, distance, stops), but that assumption has not been empirically demonstrated. Investigation of the fundamental motivators of observed preference patterns during cycling is important for understanding preference heterogeneity in the population and forecasting how energy-related interventions (e.g., evolving forms and levels of motor assistance) would influence cycling experience and behaviour. This research aims to address that knowledge gap by exploring how cyclist preferences regarding energy expenditure are reflected in their route decisions.

Methodological Approach

The objective of this research is to determine whether a measure of an individual's perceived cost of energy expenditure relative to travel time (MRS_{et}) moderates their preferences for route factors. MRS_{et}, defined as the ratio of the marginal disutility of energy expenditure (kcal/min) to the marginal disutility of travel time (min/km) [26], captures how cyclists trade off physical effort for time savings—i.e., their (un)willingness to exert more energy (pedal harder) to reduce travel time (go faster) in a given context. It is mathematically linked to cruising speed—the speed cyclists maintain in free-flow conditions—and serves as a key measure of energy expenditure preferences.

To operationalize MRS_{et}, Berjisian and Bigazzi [27] extracted cruising speed data and estimated trip-level MRS_{et} as the median value during cruising events for each trip [28] for 256 cyclists in metropolitan Vancouver, Canada, based on GPS records from 1,451 utilitarian cycling trips [29]. We build on this past work to examine how a cyclist's perceived cost of energy expenditure (individual MRS_{et} value) influences their route decisions on a given trip.

We use a structured methodological approach that combines advanced route choice modeling with energy expenditure analysis. The process involves several key steps: generating diverse route choice sets, developing a standard route choice model with latent segmentation, and incorporating two versions of the MRS_{et} variable as segmentation factors. The steps are detailed as follows:

* **Cycling Survey Data:** The dataset includes GPS records at 1-second intervals from cycling trips over 1 week from 256 participants [29]. Participants also provided trip purpose, sociodemographic information, and self-reported cycling preferences, enabling us to account for a range of individual and trip-specific factors.

* **Generating Route Alternatives:** To model route choices accurately, we generate realistic and diverse route alternatives for each trip using the Doubly Stochastic Generation Function (DSGF) [30]. This method employs a cost function that incorporates random link impedances and preference distributions, accounting for variations in cyclists' perceptions and preferences. To ensure the choice sets are both relevant and computationally manageable, we developed a calibration method that iteratively adjusts the cost function parameters. This calibration balances realism (alignment with observed routes) and heterogeneity (diversity of alternatives), ensuring the generated routes reflect real-world cycling behavior while maintaining computational efficiency.

* **Standard Route Choice Modeling:** We apply a Mixed Path Size Logit (MPSL) model within a Random Utility Maximization (RUM) framework to account for the non-independence of route alternatives and repeated choices by the same individual. The model incorporates route factors (e.g., distance, grade, infrastructure type) and cyclist/trip factors (e.g., trip purpose, gender, age). Latent Segmentation (LS) is introduced to the model to examine how cyclist and trip factors influence route preferences, with separate utility parameters for each class of cyclists [31]. Class allocation is dependent on a set of cyclist and trip factors: commute-related trip purpose, female gender, 'Dedicated' cyclist type, and age over 60 y.

* **Incorporation of Cyclists' Energy Expenditure Preferences.** We employ MRS_{et} to integrate energy expenditure preferences into the route choice framework. In the LS model, MRS_{et} is used as an additional segmentation variable to define preference classes.

One challenge is that MRS_{et} values can be influenced by route characteristics, such as steep grades, which affect the marginal disutility of energy expenditure [26], [28]. To isolate the effects of energy expenditure preferences from confounding factors already included in route choice models, we derive an idiosyncratic MRS_{et} value ($MRS_{et,id}$) that isolates individual-specific energy expenditure preferences by removing the effects of both route characteristics (e.g., grade, infrastructure) and cyclist/trip factors (e.g., gender, trip purpose). Using this idiosyncratic $MRS_{et,id}$ value allows us to assess whether explicit knowledge of energy expenditure preferences adds value beyond the energy-related effects already indirectly captured by existing variables in route choice models.

The median MRS_{et} and $MRS_{et,id}$ for each trip are included in the MPSL model as segmentation variables for latent classes. The two resulting energy-preference-sensitive model specifications are LS-MRS (which extends the Latent Segmentation model LS by using MRS_{et} as an additional segmentation variable) and LS-Id-MRS (which extends LS by using $MRS_{et,id}$ as an additional segmentation variable). For comparisons, these 3 MPSL models (LS, LS-MRS, and LS-Id-MRS) were also tested using a simpler Path Size Logit (PSL) structure that excluded the individual-level random effects for the utility coefficients.

* **Model Evaluation:** By examining the model parameter estimates across latent classes, between the 3 MPSL models, we assess whether energy expenditure preferences moderate route preferences. The parameter estimates represent the constant marginal effects of route factors on route utility. To interpret these effects meaningfully, we calculate utility-neutral trade-offs with respect to route length—indicating the proportional increase or decrease in route length required to maintain the same utility for a unit change in each variable.

Key Findings and Conclusions

This research provides the first known observational evidence supporting the hypothesis that cyclists' individual energy expenditure preferences significantly influence their route choices. More energy-conservative cyclists (i.e., those with higher $MRS_{et,id}$ values) strongly prioritize minimizing travel distance at the relative expense of other route attributes, including steeper uphill sections. While they experience greater disutility from longer routes and steeper grades, they are more likely to choose direct routes over detours—likely due to the higher time cost of detours associated with their slower riding speed. This strong preference for shorter routes also makes high-MRS riders less willing to detour to use safer cycling facilities or avoid high-risk segments. In contrast, the less energy-conservative (low-MRS) cyclists are more willing to deviate from the shortest path to avoid hills, interruptions, motor vehicle traffic, and high-risk locations.

The idiosyncratic MRS_{et} measure ($MRS_{et,id}$) appears to better represent individual energy preferences in the context of other cyclist and trip variables than the raw MRS_{et} values. However, model-derived estimates may not fully control for confounding route factors. Future research should explore controlled experiments (on fixed routes) to examine MRS_{et} variation within and between cyclists. Additional validation using alternative techniques and across different contexts and populations is also needed.

The demonstrated heterogeneity in cyclists' energy preferences, and its relationship with route preferences, has implications for designing cycling networks that appeal to a wide range of riders. To attract more energy-sensitive, high-MRS riders (often 'Casual'-type cyclists), networks should prioritize directness and avoid unpaved facilities. While flatter routes are preferred by all cyclists, detouring around hills is less appealing to energy-conservative riders. These riders are also more likely to use potentially dangerous segments if it shortens their trip—for example, along a major arterial lacking cycling infrastructure. Interventions that reduce vehicle-level energy costs (e.g., motorized (electric-assist) bicycles or efficiency-improved shared bicycles) may shift their behaviour toward safer route choices, similar to that of low-MRS riders. Energy-sensitive route choice models can help transportation professionals assess how infrastructure and vehicle-based interventions (e.g., electric-assist bicycle subsidies, improved bikeshare infrastructure) influence route decisions across different cyclist groups. Addressing diverse energy preferences should be part of creating a more accessible and appealing cycling environment for all.

This study provides foundational evidence, but more work is needed to incorporate energy preferences into utilitarian cycling analysis tools. One critical issue is distinguishing time from energy costs, which requires explicit consideration of speed choices. The steady-state speed choice model cited above can be a start, but fully distinguishing these cost components requires further development of comprehensive behavioural cycling speed models sensitive to route attributes to generate route- and cyclist-specific travel times. Another potential path forward is to develop a joint route-speed choice model that accounts for the integrated nature of route and speed decisions. That approach could be further expanded to joint speed, route, and mode choice models to investigate how energy preferences influence mode selection contingent on route options, especially in the context of emerging micromobility technologies. Such research could offer deeper insights into the adoption of sustainable transportation modes and encourage more explicit consideration of energy expenditure within urban cycling analysis.

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