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RESEARCH

Can Metro-Style Schematic Maps Induce Micromobility Ridership? A Bayesian Latent Class Ordered Logistic Analysis

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Abstract

Bicycling and other micromobility modes offer sustainable alternatives to automobile travel, yet riders often lack readable route information. Schematic micromobility maps (SMMs) apply metro-style abstraction to micromobility networks to improve legibility, but little is known about what riders want from such maps or whether access to them is associated with greater willingness to use these modes. We define schematic micromobility map inducement (SMMI) as a rider's stated increase in likelihood of using a bike, e-bike, or e-scooter when an SMM is available. Using survey data from 612 respondents, we estimate a Bayesian latent class ordered logistic model that identifies unobserved rider types and their type-specific associations with SMMI. Respondents preferred maps that were schematic and simple yet geographically legible, and reported higher SMMI when visiting an unfamiliar area than in their local context, pointing to visitor-oriented locations as priority contexts. The model recovers four rider types, *Regular Commuters*, *Fair-Weather Recreationists*, *Cautious Navigators*, and *Regular Leisure Riders*. Predicted SMMI was highest among commute-oriented and condition-sensitive riders and lowest among *Regular Leisure Riders*, whose travel depends least on map-based navigation. *Cautious Navigators*, the type reporting the strongest stated demand for map information, showed only a moderate predicted response that was estimated with the greatest uncertainty, indicating that map access alone may be insufficient when safety and traffic exposure are the primary barriers. Schematic preference was positively associated with higher SMMI across all rider types, but the relative importance of simplicity and geographic accuracy varied by type. SMMs appear most effective as a complement to infrastructure investment, targeted to settings where route uncertainty is the binding constraint on travel decisions.

Keywords Schematic maps · Wayfinding · Micromobility · Latent class ordered logistic model · Stated preferences · Cycling · Bayesian inference

Introduction

Bicycling and other micromobility modes are increasingly recognized as important components of sustainable urban transportation because they support physical activity and public health while also contributing to lower-emission urban mobility (Oja et al. 2011; Valentini et al. 2023). They also remain widely available travel modes. Globally, an estimated 42% of households own at least one bicycle (Oke et al. 2015). Yet, in many places, using these modes remains difficult because the network is hard to interpret. Riders often need to determine which routes are connected, which feel comfortable, and which are practical for a given trip, especially when traveling beyond familiar corridors or visiting an unfamiliar area.

Maps are one of the main tools through which this information is communicated. In transport cartography, schematic maps simplify geographic detail and emphasize key routes and connections, which can make network information easier to read and compare (Agrawala and Stolte 2001; Avelar and Hurni 2006; Wu et al. 2020; Galvão et al. 2021). This logic is most established in transit mapping, where a schematic representation can often prioritize connectivity without sacrificing the information most riders need. For cities seeking to expand micromobility use, improving how route networks are communicated to potential riders is a low-cost

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intervention relative to infrastructure construction, but its effectiveness depends on whether the maps actually meet rider needs.

For bicycling and micromobility, the design problem is more complex because riders evaluate not only where a route goes, but also the conditions under which it is traveled, including facility type, traffic exposure, continuity, slope, safety, amenities, and connections to destinations or other transport modes (Wessel and Widener 2015; Winters and Teschke 2010; Broach et al. 2012; Mekuria 2012; Teschke et al. 2012; Merlin et al. 2021). In this paper, we define schematic micromobility maps (SMMs) as maps that apply schematic design principles to bicycle, e-bike, e-scooter, and related low-speed travel networks while preserving the route quality information needed to judge comfort, feasibility, and practicality.

Riders also vary substantially. Prior research shows meaningful variation in comfort, confidence, infrastructure preferences, and perceived bikeability across different kinds of riders (Geller 2006; Dill and McNeil 2016; Clark et al. 2021; Aldred et al. 2017). A map that feels clear and sufficient to a confident commuter may provide insufficient reassurance or actionable detail for a more hesitant rider, an occasional user, or a visitor. SMM design should therefore be informed by differences in how riders interpret and use route information.

Despite relevant work on schematic maps, bicycle mapping, route choice, and rider heterogeneity, there is still little direct evidence on what users want from maps of this kind. To our knowledge, prior work has yet to directly survey users about the design of such maps or the features they want them to include. Design experiments and usability studies can evaluate specific map layouts, but they cannot capture how users weigh competing design tradeoffs or whether access to a map is associated with a higher stated likelihood of use across a diverse population. Evidence also remains limited on whether access to an SMM is associated with a higher likelihood of using a bike, e-bike, or e-scooter, and whether any such association differs across rider types, a question with direct implications for where and for whom SMM deployment is likely to be most effective.

This study examines these questions using survey data from 612 respondents. The analysis examines preferences over map design tradeoffs, reported barriers and information needs, and associations between these factors and respondents' stated increase in the likelihood of using a bike, e-bike, or e-scooter when an SMM is available, which we refer to as schematic micromobility map inducement (SMMI). We examine SMMI in local and visiting contexts. The paper combines descriptive evidence with a Bayesian latent class ordered logistic model (LCOLM) that identifies rider types with different map preferences and different associations with SMMI.

This study contributes new evidence on a question not previously examined with survey data at scale, using a modeling framework suited to it. We combine a latent class measurement model over behavioral and preference indicators with a class-specific ordered logistic model for stated map inducement, and estimate the two components jointly in a Bayesian framework via stochastic variational inference. Joint estimation lets the ordered outcome inform how rider types are formed, and the Bayesian treatment propagates class membership uncertainty into the type-specific associations, which we report with credible intervals rather than the point estimates typical of two-step latent class applications. The result is rider-type-specific and deployment-context-specific guidance for where schematic maps are most likely to support sustainable micromobility use.

The remainder of the paper proceeds as follows. The next section reviews the relevant work. The Methods section describes the survey, variables, and the Bayesian LCOLM framework. The Results section presents the descriptive and latent class results, the Discussion considers the implications for rider-centered SMM design and future research, and the Conclusion closes the paper.

Literature Review

Schematic maps improve network legibility by reducing visual complexity and clarifying connectivity, decision points, and route structure (Avelar and Hurni 2006; Wu et al. 2020; Galvão et al. 2021). This work has been developed primarily in transit mapping, where the central design goal is to highlight network topology while suppressing geographic detail that riders do not need for most decisions. The underlying logic applies to bicycling and micromobility, but the information demands are different. Transit riders primarily need to know where routes go and where to transfer. Micromobility riders also need to judge whether a route feels safe, comfortable, and practical for a given trip.

Route choice research establishes why this distinction matters for map design. Facility separation, low-stress conditions, route continuity, and safety all shape whether a route is perceived as usable (Winters and Teschke 2010; Broach et al. 2012; Mekuria 2012; Teschke et al. 2012; Merlin et al. 2021). Recent work sharpens this point. In a comparative study of cyclist route choice models, Meister et al. (2024) show that cycling infrastructure, lower-speed streets, traffic signals, and gradient are central route quality attributes, even though estimated effect sizes vary across model specifications. Latvala et al. (2026) further show that slope sensitivity differs by bicycle type, with conventional cyclists tending to prefer shorter and flatter routes while e-bike users are more tolerant of steeper gradients. Gan et al. (2023), although focused on bike mode choice rather than route choice, complements

this evidence by incorporating route-level uphill gradient and lane/speed-based road-condition proxies in Switzerland; their results suggest that uphill gradient matters more than the road-condition proxies, while the lane-based proxy points to greater sensitivity to traffic volume than to speed among those route-level conditions. Route-level analyses further show that the presence of bicycle facilities shifts mode choice, suggesting that maps intended to support micromobility should make route conditions legible rather than treating all network links as equivalent (Hwang and Guhathakurta 2013). Recent work also shows that cycling behavior depends not only on objective built-environment features but also on street-level perceptual qualities (Rui and Xu 2024) and that bikeability can be assessed at the segment level using observed cycling behavior (Wang et al. 2024). Newer route choice evidence implies that map content should extend beyond network geometry and facility type to include simplified information on gradient and motorized traffic exposure, while recognizing that the salience of these attributes may vary across rider groups and vehicle types. Together, this body of evidence implies that a useful map for bicycling and micromobility must convey information riders use to assess comfort, feasibility, and route quality, not just network geometry.

Existing bicycle map research has approached these design challenges primarily through design frameworks, prototype comparisons, and usability experiments (Wessel and Widener 2015; Galvão et al. 2021; Bauer and Ludwig 2019; Meilinger et al. 2006; Büchel and Reichenbacher 2023; Abdalazeem et al. 2026). A recurring finding is that abstraction can improve navigation task performance, while additional detail tends to increase visual complexity and clutter (Galvão et al. 2021; Bauer and Ludwig 2019; Meilinger et al. 2006; Büchel and Reichenbacher 2023). A related concern is that bicycle maps often rely on subjective judgments about route quality that may not reflect how different riders define comfort or usefulness (Wessel and Widener 2015). These studies clarify specific design tradeoffs but focus more on map performance than on how users themselves evaluate those tradeoffs or what they want a map to include.

Rider heterogeneity adds further complexity. Comfort, confidence, infrastructure preferences, and perceived bikeability vary systematically across users (Cabral and Kim 2020; Dill and McNeil 2016; Clark et al. 2021; Aldred et al. 2017). Wayfinding research similarly shows that individuals differ in how they process spatial information and rely on navigational aids (Zomer et al. 2019; Vandenberg et al. 2016). A design that feels clear and sufficient to a confident, regular rider may provide inadequate reassurance or actionable detail for a more hesitant one. These differences suggest that map design for micromobility should account for variation in how riders interpret and use route information.

These differences in rider behavior also motivate the choice of modeling framework. Latent class models have become a standard tool for recovering unobserved heterogeneity in transportation behavior, segmenting a population into classes with distinct preference parameters while jointly estimating class membership and outcome probabilities (Greene and Hensher 2003; Kim and Mokhtarian 2023). This framework has been applied directly to cycling research to identify how built-environment conditions affect different subgroups of cyclists (Oliva et al. 2018), to model safety as a perceptual latent variable in cycling infrastructure assessment (Rossetti et al. 2018), and to analyze how accident risk varies across latent environment typologies (Costa et al. 2024). In micromobility specifically, latent class choice models have been used with stated preference data to uncover segments with distinct sensitivities to service attributes and mode shift potential (Ghasri et al. 2024; Wu et al. 2025). Extensions of the base framework have relaxed the standard parametric class membership specification, replacing it with mixture models or Gaussian processes to better capture nonlinear heterogeneity while preserving the interpretability of class-specific estimates (Sfeir et al. 2022). This body of work demonstrates the value of jointly estimating class membership and outcomes in transportation contexts, but its application to map preferences and stated micromobility inducement has not been explored.

Despite this body of work, several user-centered questions remain open. Prior research has not directly surveyed users about the design of SMMs or the features they want such maps to include. It is also unclear how users weigh the main design tradeoffs—schematic versus geographic representation, simplicity versus completeness, and which route attributes to prioritize. Survey-based evidence is also limited on whether access to an SMM is associated with a higher stated likelihood of micromobility use, and whether any such association differs across rider groups. This study addresses these questions by examining map preferences, perceived barriers, information needs, and stated micromobility map inducement (SMMI) using a latent class ordered outcome framework.

Methods

Data

Survey Administration and Analytic Sample

We used a structured online survey developed for research on schematic micromobility maps (SMMs) and their relationship to stated micromobility use. The survey was administered through Qualtrics from May 29 to August 31, 2025 (94 days). Recruitment combined online distribution with printed flyers containing QR codes, and respondents who completed the survey were offered a $7 gift card. Because the

survey was monetarily incentivized and openly distributed, it attracted substantial automated (bot) traffic. The platform recorded 12,020 submissions over the field period, including a single-day spike of 3951 submissions (32.9%) that was clearly inconsistent with organic recruitment.

To secure the dataset, we applied the transparent, multi-filter bot-detection pipeline developed and validated in our companion study (Ruger et al. 2026). The pipeline applies 11 independent filters across 4 categories: platform-generated risk signals (reCAPTCHA score, composite fraud score, and ambiguous free-text flags), identity and duplication checks, behavioral interaction patterns (click counts, page-level and survey-level timing, and duplicate temporal patterns), and device consistency (browser, operating system, and screen-resolution coherence). An entry was removed if it failed any single filter. The pipeline removed 94.8% of submissions, and its decisions were validated against an independent blind expert review (88.9% agreement) and an explainable XGBoost classifier that reproduced the rule-based labels with an F1-score of 0.94. Full filter definitions, thresholds, sensitivity analyses, and ablation tests are reported in Ruger et al. (2026). The per-stage reduction is summarized in Table 8. Applying the pipeline yielded 620 valid responses, of which 612 had complete responses on all variables used in this paper and constitute the analytic sample ($N = 612$). The retained responses were geographically dispersed across the United States. Submission timing and the spatial distribution of response locations are shown in Fig. 1.

Survey Instrument and Analytic Variables

The survey was organized into three substantive blocks covering demographics, bike ownership and usage, and map preferences, preceded by the consent form and schematic map example, as summarized in Table 1. Question formats included single-choice items, multi-select items, Likert-scale statements, and optional free-text responses.

Before the map preference questions, all respondents were shown a side-by-side comparison of geographic and schematic representations of the Boston MBTA subway network (Fig. 2), with the prompt: *"Schematic maps simplify complex networks by focusing on clarity, not geographic accuracy."*

The map preference block included three SMM design-related preference items and two SMMI outcome items, all rated on five-point Likert scales from *strongly disagree* to *strongly agree*. The three preference items measure distinct design dimensions. Geographic accuracy (Q15) concerns spatial fidelity: whether the map preserves correct road geometry and distances. Simplicity over completeness (Q16) concerns information density: whether the map limits the number of displayed elements rather than providing exhaustive coverage. Schematic preference (Q17) concerns the visual representation style: whether the map uses metro-style abstraction rather than a geographically projected layout. The exact question wording was as follows:

1. *Geographic accuracy* (Q15): "A bike/e-bike/e-scooter map should be as geographically accurate as possible (e.g., showing exact road layouts and distances between locations)."
2. *Simplicity over completeness* (Q16): "I would prefer a bike/e-bike/e-scooter map that is simple to one with complete information (e.g., every route, stop, points of interest)."
3. *Schematic preference* (Q17): "I would prefer a schematic [metro/subway-style] map of bike/e-bike/e-scooter routes to a geographically accurate one."

The two SMMI outcome items were also rated on five-point Likert scales:

1. *Local SMMI* (Q18): "I would be more likely to use a bike/e-bike/e-scooter if a schematic [metro/subway-style] map of relevant routes were posted at various locations around the area I live."
2. *Visiting SMMI* (Q19): "I would be more likely to use a bike/e-bike/e-scooter if a schematic [metro/subway-style] map of relevant routes were available in an area I was visiting."

The local SMMI outcome (Q18) was used as the main ordered outcome in the LCOLM, while the visiting SMMI outcome (Q19) was analyzed descriptively. For modeling, the five-point SMMI item was treated as an ordered outcome with K = 5 categories running from strongly disagree to strongly agree. Model-based SMMI scores are reported on a 0 to 4 scale, where 0 corresponds to strongly disagree and 4 to strongly agree, while descriptive Likert means are reported on the original 1 to 5 scale. For analysis, multi-select responses were converted to binary indicators, while single-response items were retained in categorical form in the cleaned survey dataset and recoded into grouped or binary variables where needed for modeling. These analytic variables captured reported trip purposes, perceived barriers, seasonal or weather effects, desired map content, intended trip types for map use, and selected respondent characteristics and travel behaviors. Optional free-text responses were retained in the dataset but excluded from the latent class model reported in this paper. The full survey is reproduced in Appendix A.

Descriptive Overview of the Analytic Sample

We summarize the analytic sample in Table 2, alongside U.S. population benchmarks from the American Community Sur-

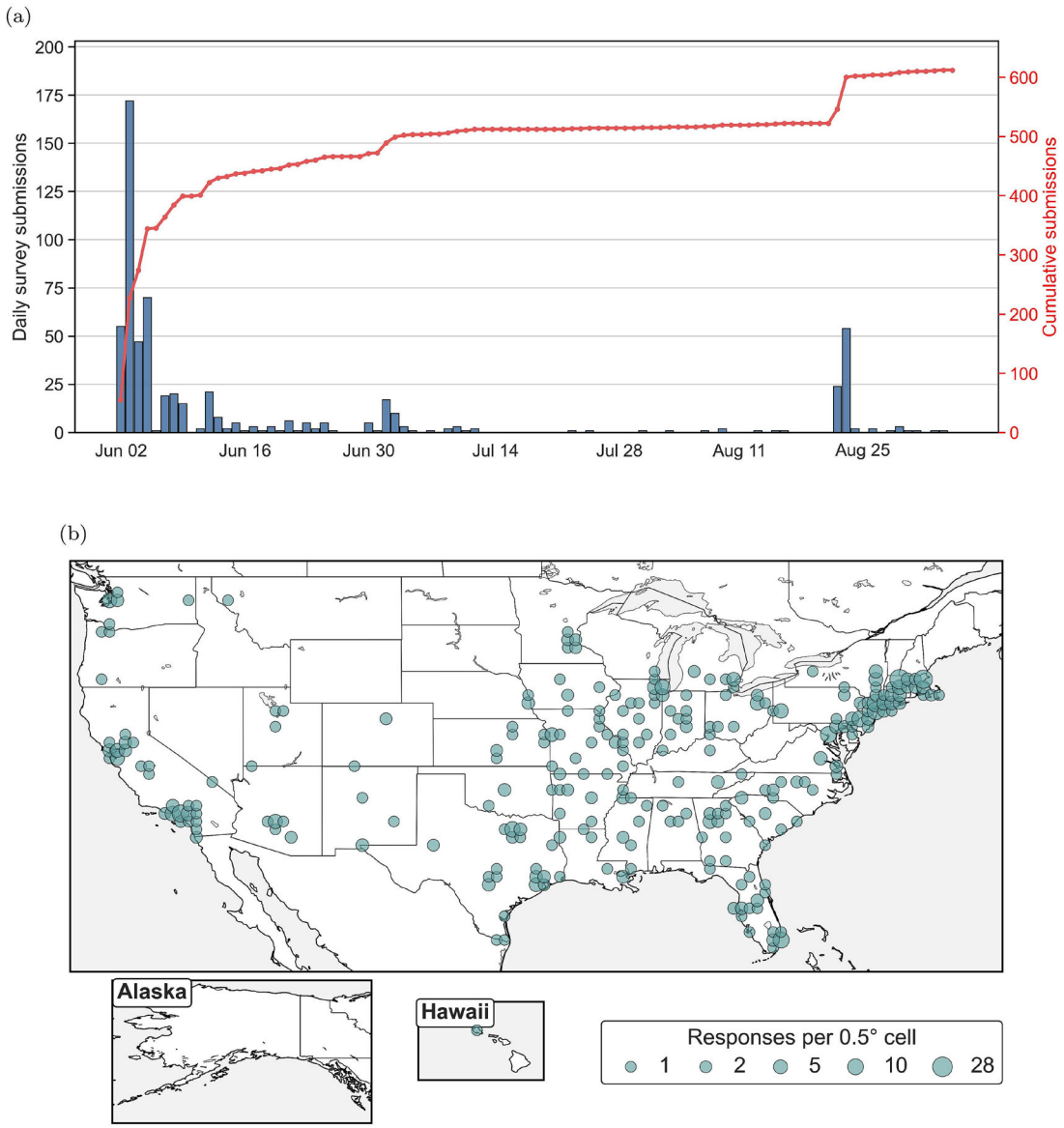
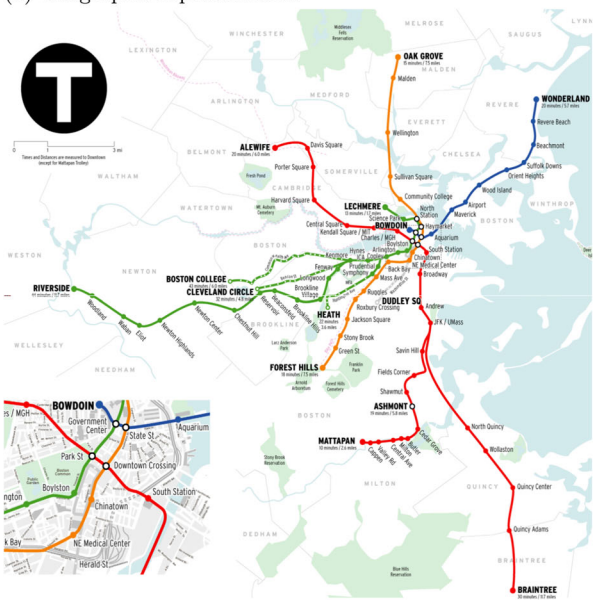


Fig. 1 Survey administration overview: **a** verified survey submissions over the study period and **b** spatial distribution of response locations

vey (ACS). The sample skewed younger than the U.S. adult population, with 68.8% of respondents under the age of 35 compared with 29.2% nationally. Most respondents identified as male (59.2% versus 49.0% nationally), and 30.9% reported being students. Household sizes were larger than the national distribution, with 83.8% reporting three or more household members compared with 37.4% of U.S. households. Car access was common, although the 17.3% reporting no household vehicle was roughly double the national share of zero-vehicle households (8.4%). The sample was also considerably more micromobility-oriented and map-engaged than the general population: 72.9% reported using a bike, e-bike, or e-scooter often or always and 72.7% reported using a bike-share service, whereas nationally representative travel data indicate that cycling accounts for only about 1% of all trips in the United States (NHTS 2017). Similarly, 62.1% reported using smartphone route mapping often or always. Preferred access to SMMs was mainly digital or mixed: 60.3% preferred digital maps, 31.7% preferred both digital and physical access, while only 8.0% preferred physical maps alone. These comparisons indicate that the sample is not representative of the general U.S. population but instead over-represents engaged micromobility users. We therefore interpret our findings as evidence of behavioral mechanisms among an engaged-user population rather than as population-level prevalence estimates.

(a) Geographic representation



(b) Schematic representation



Fig. 2 Boston MBTA subway network as displayed to survey respondents (Q2): geographic (left) and schematic (right) representations

Table 1 Survey question categories and topics

Category	Questions	Topics covered
Introductory materials	Q1–Q2	Informed consent
		Schematic map example
Schematic map example demographics	Q3–Q7	Age range
		Gender identity
		Student status
		Household size
		Car availability
Car availability bike ownership and usage	Q8–Q13	Usage frequency
		Trip purpose
		Household bike/e-bike/e-scooter availability
		Bike-share use
		Reported barriers to greater use
		Seasonal and weather effects
Map preferences and attitudes	Q14–Q23	Smartphone route-mapping frequency
		Geographic accuracy preference
		Simplicity versus completeness
		SMM preference
		Local and visiting SMMI outcomes
		Important map content
		Trip types for map use
		Digital versus physical SMM access preference
		Open-ended map content suggestions

Table 2 Key characteristics of the analytic sample ($N = 612$) with U.S. population benchmarks

Domain	Response category	Count	Sample (%)	Pop. (%)
Age range	18–24 years	148	24.2	11.7
	25–34 years	273	44.6	17.5
	35–44 years	108	17.6	16.9
	45–54 years	42	6.9	15.6
	55–64 years	24	3.9	16.2
	65 years or greater	14	2.3	22.0
Gender	Female	241	39.4	51.0
	Male	362	59.2	49.0
	Non-binary	2	0.3	–
Student status	Yes	189	30.9	–
	No	413	67.5	–
Household size	1 person	29	4.7	28.7
	2 people	69	11.3	33.8
	3 people	229	37.4	15.3
	4+ people	284	46.4	22.1
Cars available	0 cars	106	17.3	8.4
	1 car	272	44.4	33.1
	2 cars	207	33.8	36.6
	3+ cars	27	4.4	21.9
Micromobility use	Never	6	1.0	–
	Sometimes	155	25.3	–
	Often	309	50.5	–
	Always	137	22.4	–
Micromobility vehicles	0 available	99	16.2	–
	1 available	259	42.3	–
	2 available	180	29.4	–
	3+ available	74	12.1	–
Bike-share use	Yes	445	72.7	–
	No	166	27.1	–
Route mapping use	Never	27	4.4	–
	Sometimes	202	33.0	–
	Often	233	38.1	–
	Always	147	24.0	–
Preferred SMM access	Physical maps	49	8.0	–
	Digital maps	369	60.3	–
	Both digital and physical	194	31.7	–
SMM preferences and	Prefer geographic accuracy	456	74.5	–
SMMI outcomes	Prefer simpler maps	422	69.0	–
	Prefer schematic maps	418	68.3	–
	Higher local SMMI	432	70.6	–
	Higher visiting SMMI	488	79.7	–

Sample percentages are computed over N. For the final block, percentages refer to respondents who agreed or strongly agreed with each SMM preference or SMMI outcome statement. Population benchmarks are U.S. Census Bureau American Community Survey 2020–2024 5-year estimates

Bayesian Latent Class Ordered Logistic Model (LCOLM)

We estimated a latent class ordered logistic model (LCOLM) to account for unobserved heterogeneity in survey responses. Latent class models recover discrete population segments by jointly estimating class membership and outcome parameters, allowing preference heterogeneity to be represented without assuming a continuous parametric mixing distribution (Greene and Hensher 2003; Kim and Mokhtarian 2023). The LCOLM identifies unobserved respondent classes from binary indicators describing map preferences, micromobility use, barriers, and related behaviors, while simultaneously estimating how respondent attributes are associated with the ordered SMMI outcome within each class. Because the class membership and ordered outcome components are estimated jointly, the resulting classes reflect both indicator patterns and differences in SMMI.

We estimated the LCOLM in a Bayesian framework, which allows for prior specification and reports posterior distributions rather than point estimates. This approach propagates uncertainty throughout the full joint model and provides uncertainty quantification for both class membership and the model parameters.

A plate diagram of the LCOLM is shown in Fig. 3. For respondent n, let $\boldsymbol{w}_n = (w_{n1}, \ldots, w_{nD})$ denote the D observed binary survey indicators (e.g., whether a respondent rides regularly, uses bike-share, or reports safety concerns), with $w_{nd} \in \{0, 1\}$. Let $\boldsymbol{x}_n$ denote the predictors in the ordered outcome model, let $y_n \in \{1, \ldots, K\}$ denote the ordered SMMI outcome, and let $z_n \in \{1, \ldots, C\}$ denote the latent class membership indicator.

Latent class membership is modeled as

$$z_n \mid \boldsymbol{\pi} \sim \text{Categorical}(\pi_1, \ldots, \pi_C), \tag{1}$$

where $\boldsymbol{\pi} = (\pi_1, \ldots, \pi_C)$ are the class proportions, with $\sum_{c=1}^{C} \pi_c = 1$.

Within each class, the binary indicators are modeled as independent Bernoulli draws with class-specific indicator probabilities:

$$w_{nd} \mid z_n = c \sim \text{Bernoulli}(\mu_{dc}), \qquad d = 1, \ldots, D, \tag{2}$$

so that

$$p(\boldsymbol{w}_n \mid z_n = c) = \prod_{d=1}^{D} \mu_{dc}^{w_{nd}} (1 - \mu_{dc})^{1 - w_{nd}}. \tag{3}$$

The ordered SMMI outcome is modeled using a class-specific ordered logistic regression. We introduce an underlying latent propensity

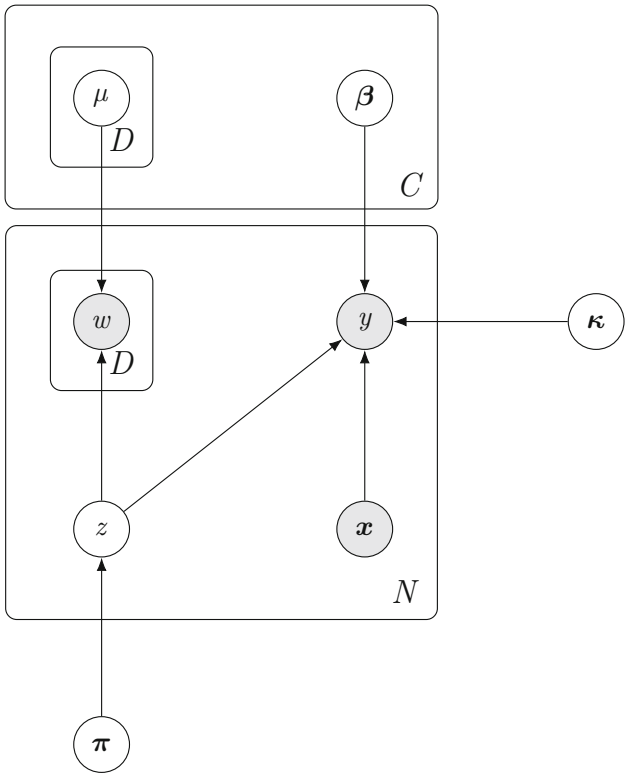


Fig. 3 Plate notation for the LCOLM. Shaded nodes denote observed variables (w: observed binary survey indicators; $\boldsymbol{x}$: predictor variables; y: ordered SMMI outcome); unshaded nodes denote latent variables and parameters (z: latent class assignment; μ, $\boldsymbol{\beta}$, $\boldsymbol{\pi}$, $\boldsymbol{\kappa}$: model parameters). Node w represents observed survey responses used to infer class membership, while z is the latent class variable itself. Node labels denote indexed quantities replicated by the surrounding plates

$$y_n^* = \boldsymbol{x}_n^\top \boldsymbol{\beta}_c + \varepsilon_n, \tag{4}$$

for respondent n in class c, where $\boldsymbol{\beta}_c$ is the class-specific coefficient vector and

$$\varepsilon_n \sim \text{Logistic}(0, 1), \qquad F_\varepsilon(u) = \frac{1}{1 + \exp(-u)}. \tag{5}$$

The observed ordered response is determined by shared cutpoints $\kappa_1, \ldots, \kappa_{K-1}$:

$$y_n = k \iff \kappa_{k-1} < y_n^* \le \kappa_k, \qquad k = 1, \ldots, K, \tag{6}$$

with $\kappa_0 = -\infty$, $\kappa_K = +\infty$, and $\kappa_1 < \cdots < \kappa_{K-1}$.

This implies cumulative probabilities

$$\begin{aligned} p(y_n \le k \mid \boldsymbol{x}_n, z_n = c) &= \boldsymbol{\sigma}\left(\kappa_k - \boldsymbol{x}_n^\top \boldsymbol{\beta}_c\right) \\ &= \frac{1}{1 + \exp\left[-\left(\kappa_k - \boldsymbol{x}_n^\top \boldsymbol{\beta}_c\right)\right]}, \\ & \quad k = 1, \ldots, K - 1, \end{aligned} \tag{7}$$

where $\sigma(u) = (1+\exp(-u))^{-1}$ is the logistic function. Thus, the class-specific probability of observing category k is

$$p(y_n = k \mid \boldsymbol{x}_n, z_n = c) = \sigma\left(\kappa_k - \boldsymbol{x}_n^\top \boldsymbol{\beta}_c\right) - \sigma\left(\kappa_{k-1} - \boldsymbol{x}_n^\top \boldsymbol{\beta}_c\right). \quad (8)$$

Prior Specification

We placed a Dirichlet prior on the class proportions,

$$\boldsymbol{\pi} \sim \text{Dirichlet}(\boldsymbol{\alpha}), \quad (9)$$

where $\boldsymbol{\alpha} = (\alpha_1, \ldots, \alpha_C)$ are the concentration parameters.

Independent Beta priors were placed on the class-specific Bernoulli probabilities,

$$\mu_{dc} \sim \text{Beta}(a, b), \qquad d = 1, \ldots, D,\ c = 1, \ldots, C, \quad (10)$$

where $a > 0$ and $b > 0$ are Beta shape parameters.

For the class-specific ordered-logit coefficients, we used weakly informative Normal priors:

$$\boldsymbol{\beta}_c \sim \mathcal{N}(\mathbf{0}, \sigma_\beta^2 \boldsymbol{I}), \qquad c = 1, \ldots, C, \quad (11)$$

where $\sigma_\beta > 0$ is a scale hyperparameter and $\boldsymbol{I}$ is the identity matrix.

To ensure that the shared cutpoints were ordered, we placed a Normal prior on the first cutpoint and HalfNormal priors on the positive increments (δ_k) used to construct the remaining cutpoints. Thus,

$$\kappa_1 \sim \mathcal{N}(0, \sigma_\kappa^2), \quad (12)$$

$$\delta_k \sim \text{HalfNormal}(\sigma_\delta), \qquad k = 2, \ldots, K-1, \quad (13)$$

$$\kappa_k = \kappa_{k-1} + \delta_k, \quad (14)$$

where $\sigma_\kappa > 0$ and $\sigma_\delta > 0$ are the scale hyperparameters. This construction guarantees $\kappa_1 < \cdots < \kappa_{K-1}$.

These priors were weakly informative and helped regularize estimation by discouraging unstable solutions, such as extreme class-specific probabilities or weakly separated classes. All prior parameters (hyperparameters) are summarized in Table 3.

Likelihood and Posterior

Let $\boldsymbol{\Theta} = \{\boldsymbol{\pi}, \boldsymbol{\mu}, \boldsymbol{\beta}_{1:C}, \boldsymbol{\kappa}\}$ collect all unknown parameters, where $\boldsymbol{\mu} = \{\mu_{dc}\}_{d=1:D,\, c=1:C}$ and $\boldsymbol{\beta}_{1:C} = \{\boldsymbol{\beta}_c\}_{c=1:C}$. Conditional on class membership, we assume local independence, so that the binary indicators are mutually independent, as in Eq. (3), and are also independent of the ordered outcome:

$$p(\boldsymbol{w}_n, y_n \mid z_n = c, \boldsymbol{x}_n, \boldsymbol{\Theta}) = p(\boldsymbol{w}_n \mid z_n = c, \boldsymbol{\mu})\ p(y_n \mid z_n = c, \boldsymbol{x}_n, \boldsymbol{\beta}_c, \boldsymbol{\kappa}). \quad (15)$$

Marginalizing over the latent class gives the observed-data contribution for respondent n:

$$p(\boldsymbol{w}_n, y_n \mid \boldsymbol{x}_n, \boldsymbol{\Theta}) = \sum_{c=1}^{C} \pi_c\ p(\boldsymbol{w}_n \mid z_n = c, \boldsymbol{\mu})\ p(y_n \mid z_n = c, \boldsymbol{x}_n, \boldsymbol{\beta}_c, \boldsymbol{\kappa}). \quad (16)$$

Assuming respondents are independent, the full data likelihood is

$$p(\boldsymbol{W}, \boldsymbol{y} \mid \boldsymbol{X}, \boldsymbol{\Theta}) = \prod_{n=1}^{N} \sum_{c=1}^{C} \pi_c\ p(\boldsymbol{w}_n \mid z_n = c, \boldsymbol{\mu})\ p(y_n \mid z_n = c, \boldsymbol{x}_n, \boldsymbol{\beta}_c, \boldsymbol{\kappa}). \quad (17)$$

The posterior distribution is then

$$p\left(\boldsymbol{\Theta} \mid \boldsymbol{W}, \boldsymbol{y}, \boldsymbol{X}\right) = \frac{1}{Z} p\left(\boldsymbol{W}, \boldsymbol{y} \mid \boldsymbol{X}, \boldsymbol{\Theta}\right)\ p(\boldsymbol{\pi})\ p(\boldsymbol{\mu})\ p(\boldsymbol{\kappa}) \prod_{c=1}^{C} p(\boldsymbol{\beta}_c), \quad (18)$$

where Z is the normalization constant (marginal likelihood) defined as

$$Z = \int p\left(\boldsymbol{W}, \boldsymbol{y} \mid \boldsymbol{X}, \boldsymbol{\pi}, \boldsymbol{\mu}, \boldsymbol{\beta}_{1:C}, \boldsymbol{\kappa}\right)\ p(\boldsymbol{\pi})\ p(\boldsymbol{\mu})\ p(\boldsymbol{\kappa}) \prod_{c=1}^{C} p(\boldsymbol{\beta}_c) d\boldsymbol{\pi}\, d\boldsymbol{\mu}\, d\boldsymbol{\beta}_{1:C}\, d\boldsymbol{\kappa}. \quad (19)$$

Every model-based quantity we report carries a posterior distribution rather than a point estimate because the full joint model is estimated in this Bayesian framework. We summarize the variational posterior in three ways. First, we report 95% credible intervals for all class-specific coefficients and odds ratios, and we assess credibility against a region of practical equivalence (ROPE) rather than a point null at zero, treating an association as credible when at least 95% of its posterior mass falls outside the ROPE in the direction of the posterior mean (Higher SMMI Was Associated with Schematic Preference Across All Rider Types). Second, we propagate parameter uncertainty into derived quantities by computing them on each posterior draw, which yields credible intervals for class shares, type-level expected SMMI, and the probability of a high SMMI response. Third, the posterior supports direct probability statements about between-type contrasts, such as the probability that one rider type has higher expected SMMI than another.

Table 3 Priors used in the LCOLM

Parameter	Prior family	Hyperparameter values	Justification
Class proportions $\boldsymbol{\pi}$	Dirichlet($\boldsymbol{\alpha}$)	$\alpha_c = 1,\ \forall c$	Uninformative
Bernoulli probabilities μ_{dc}	Beta(a, b)	$a = 2,\ b = 2$	Weakly informative; discourages extreme probabilities near 0 or 1
Ordered-logit coefficients $\boldsymbol{\beta}_c$	$\mathcal{N}(\mathbf{0}, \sigma_\beta^2 \boldsymbol{I})$	$\sigma_\beta = 1$	Weakly informative; regularizes class-specific coefficient estimates toward zero
First cutpoint κ_1	$\mathcal{N}(0, \sigma_\kappa^2)$	$\sigma_\kappa = 1$	Weakly informative
Cutpoint increments δ_k	HalfNormal(σ_δ)	$\sigma_\delta = 1$	Enforces positive increments and therefore ordered cutpoints

Model Estimation

Let $q_{\boldsymbol{\psi}}(\boldsymbol{\Theta})$ denote the variational approximation to the posterior $p(\boldsymbol{\Theta} \mid \boldsymbol{W}, \boldsymbol{y}, \boldsymbol{X})$, indexed by variational parameters $\boldsymbol{\psi}$. Estimation proceeds by maximizing the evidence lower bound (ELBO),

$$\mathcal{L}(\boldsymbol{\psi}) = \mathbb{E}_{q_{\boldsymbol{\psi}}(\boldsymbol{\Theta})}\left[\log p(\boldsymbol{W}, \boldsymbol{y}, \boldsymbol{\Theta} | \boldsymbol{X}) - \log q_{\boldsymbol{\psi}}(\boldsymbol{\Theta})\right], \quad (20)$$

which is equivalent to minimizing the Kullback–Leibler divergence between the variational posterior and the true posterior (Jordan et al. 1998; Blei et al. 2017). This was done via stochastic variational inference (SVI) (Hoffman 2013; Blei et al. 2017) using the NumPyro package in Python (Phan et al. 2019) and convergence was monitored via the ELBO trajectory for the selected final model.

To enumerate classes, we fit candidate models with $C = 1, \ldots, 10$, where the single-class model ($C = 1$) is a pooled ordered logistic regression with no latent heterogeneity and serves as a baseline for whether multiple classes are warranted. For each C, we used multiple random starts to reduce sensitivity to initialization and retained the best converged run for between-model comparison. Across candidate class counts, we then compared the best-ELBO solutions using the final ELBO loss together with the Bayesian Information Criterion (BIC) and the Integrated Completed Likelihood Bayesian Information Criterion (ICL-BIC), computed from the fitted observed-data likelihood (Schwarz 1978; Biernacki et al. 2000). Lower ELBO loss and lower BIC and ICL-BIC were taken to indicate better support.

The four-class solution was preferred because it minimized both BIC and ICL-BIC while retaining interpretable classes without very small fragments. It was also strongly preferred over the single-class baseline (BIC 15,796 versus 16,279), which confirms that the data support latent heterogeneity over a homogeneous population. Final ELBO loss also improved through four classes and showed diminishing improvement thereafter. These results supported retaining $C^* = 4$. The class enumeration results are summarized in Fig. 4a.

After choosing the preferred class count, $C^* = 4$, we refit the selected model on the full sample using repeated random starts. We assessed stability by comparing the final ELBO loss, information criteria, and class assignment diagnostics across refits, and retained one solution from among the stable runs.

Posterior class probabilities were then computed for each respondent as

$$r_{nc} = p(z_n = c \mid \boldsymbol{w}_n, \boldsymbol{x}_n, y_n), \quad (21)$$

which reflects the extent to which class c explains both the respondent's binary indicator profile and observed SMMI outcome. These posterior probabilities were used to summarize class prevalence and class-specific outcome distributions. For descriptive interpretation and reporting, respondents were also assigned to the class with the highest posterior probability.

As a final model check, posterior predictive outcome proportions were compared with the observed outcome distribution. This step evaluates whether the fitted model reproduces the main empirical pattern of the ordered SMMI outcome. The observed and model-implied outcome distributions used for this posterior predictive assessment are shown in Fig. 4b.

Results

The results are organized in two parts. We first report descriptive preferences and SMMI outcomes at the sample level, and then the model results: the four latent rider types, their predicted SMMI, and the within-type associations between respondent characteristics and SMMI.

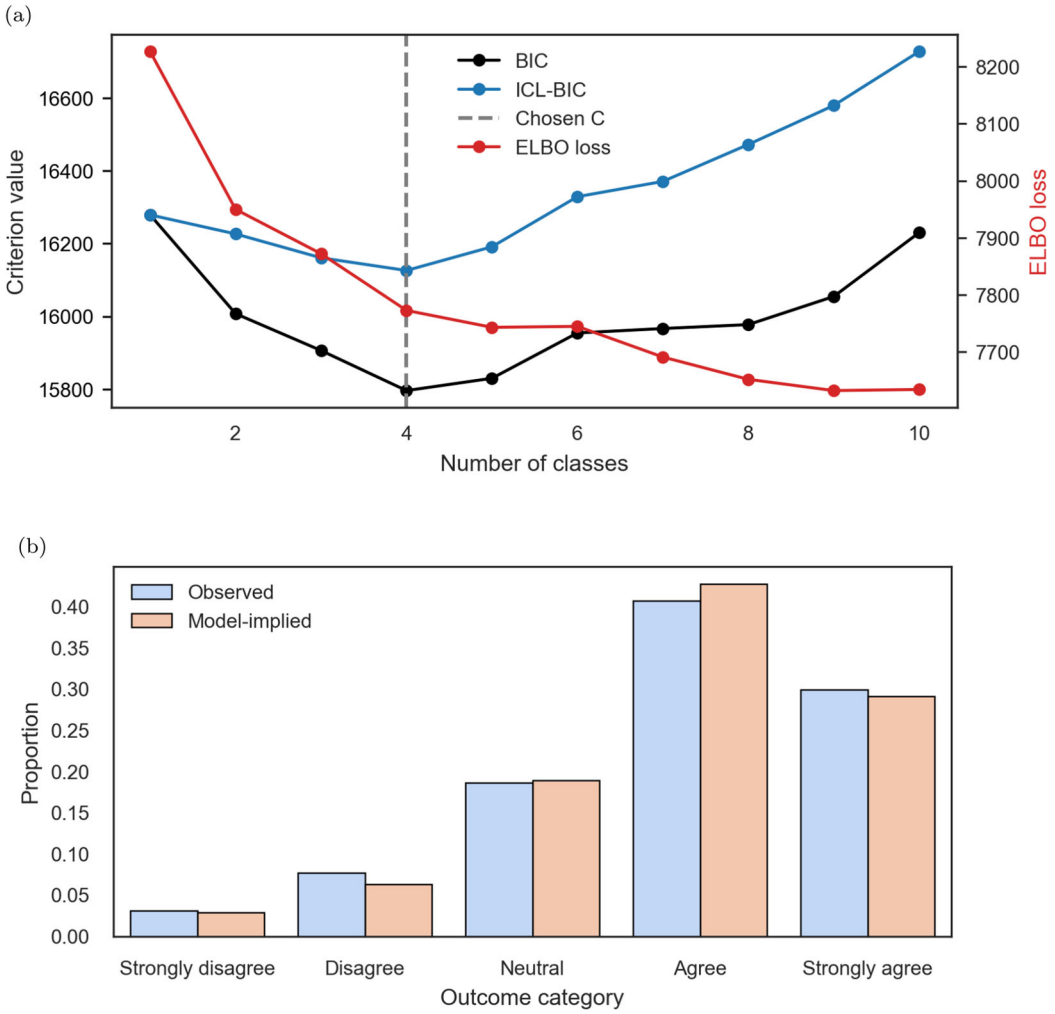


Fig. 4 Estimation diagnostics: **a** BIC, ICL-BIC, and final ELBO loss across candidate class counts, with the selected four-class solution indicated by the vertical dashed line, and **b** observed and model-implied outcome distributions for the ordered SMMI outcome

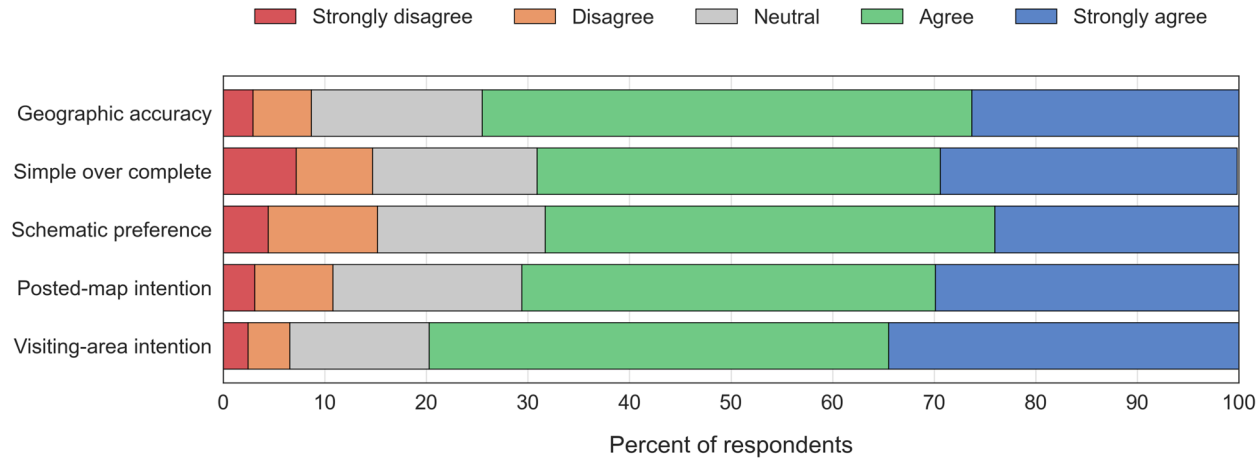


Fig. 5 Map preferences and SMMI outcomes

Descriptive Results

Respondents Preferred Maps that Were Schematic and Simple but Still Geographically Legible

Figure 5 shows strong support for all three design preferences. A total of 74.5% of respondents agreed or strongly agreed that an SMM should remain geographically accurate, 69.0% preferred simpler maps over more complete ones, and 68.3% preferred a schematic representation over a geographically accurate one. Among the 611 respondents who answered all three items, a Cochran's Q test rejected equality of the three endorsement rates ($Q = 9.83$, $p = 0.007$). Holm-corrected pairwise McNemar tests showed that geographic accuracy was endorsed at a small but significant margin over both simplicity (5.6 percentage points, $p = 0.034$) and schematic preference (6.4 percentage points, $p = 0.014$), while simplicity and schematic preference did not differ (0.8 percentage points, $p = 0.76$). The differences among the three are therefore modest, and all three remained clear majority preferences. These preferences were also held jointly. As reported in Table 4, the most common response profile was in agreement with all three statements (46.6%), and a majority (56.6%) agreed both that the map should be geographically accurate and that they preferred a schematic representation. Only 8.3% disagreed with all three. Respondents therefore did not treat schematic abstraction and geographic accuracy as competing goals. They favored maps that simplify network presentation while remaining geographically interpretable.

Respondents Reported Higher SMMI when Visiting than in Their Local Area

A majority agreed or strongly agreed that they would be more likely to use a bike, e-bike, or e-scooter if a schematic (metro-style) map were available, both around the area where they live and when visiting another place (Fig. 5). Agreement was higher in the visiting context (79.7%) than in the local context (70.6%), a difference of 9.1 percentage points (pp). The visiting context also had a higher mean Likert score (4.05 vs. 3.87), and the paired difference was statistically significant ($t(611) = 4.94$, $p < 0.001$). This gap is consistent with SMMs being especially useful when riders have less local knowledge of route continuity, comfort, and network structure.

SMMI was Higher Among Frequent Map Users and Those Preferring Mixed Access

The multi-response items help explain why respondents saw value in this kind of map. As summarized in Fig. 6, micromobility use was associated with several common trip purposes, especially recreation (75.8%), shopping (70.8%), and commuting (65.8%). Respondents also reported several persistent barriers to greater use, led by weather (69.4%), safety concerns (54.7%), and infrastructure limitations (37.7%). Their most desired map content closely matched these constraints, with especially high demand for points of interest (68.3%), infrastructure type (62.9%), and amenities (57.0%). Intended SMM use was similarly broad, spanning recreation, daily commuting, errands, and touring new areas. Respondents viewed SMMs as both navigation tools and resources for evaluating route conditions, available facilities, and the practical feasibility of different trip types.

SMMI differed significantly by smartphone route-mapping frequency and by preferred map access (Fig. 7). Respondents who used smartphone route mapping more frequently generally reported higher SMMI ($F(3, 605) = 5.82$, $p < 0.001$). Holm-adjusted pairwise comparisons showed lower SMMI among respondents who never used route mapping than among those who used it often ($p = 0.023$), and lower SMMI among those who used it sometimes than among those who used it often ($p = 0.003$). SMMI also differed by preferred map access ($F(2, 609) = 7.09$, $p < 0.001$), with respondents preferring both digital and physical access reporting higher SMMI than those preferring physical-only access ($p = 0.020$) or digital-only access ($p = 0.028$). Descriptive heterogeneity in SMMI was tied more closely

Table 4 Joint distribution of agreement with the three SMM design preference items

Geographic accuracy	Simplicity	Schematic	Count	Percent (%)
✓	✓	✓	285	46.6
✓	–	✓	61	10.0
✓	✓	–	58	9.5
✓	–	–	52	8.5
–	–	–	51	8.3
–	✓	✓	46	7.5
–	✓	–	33	5.4
–	–	✓	25	4.1

A check mark indicates the respondent agreed or strongly agreed. The joint and paired analyses use the 611 respondents who answered all three items while one respondent with a missing simplicity response is excluded

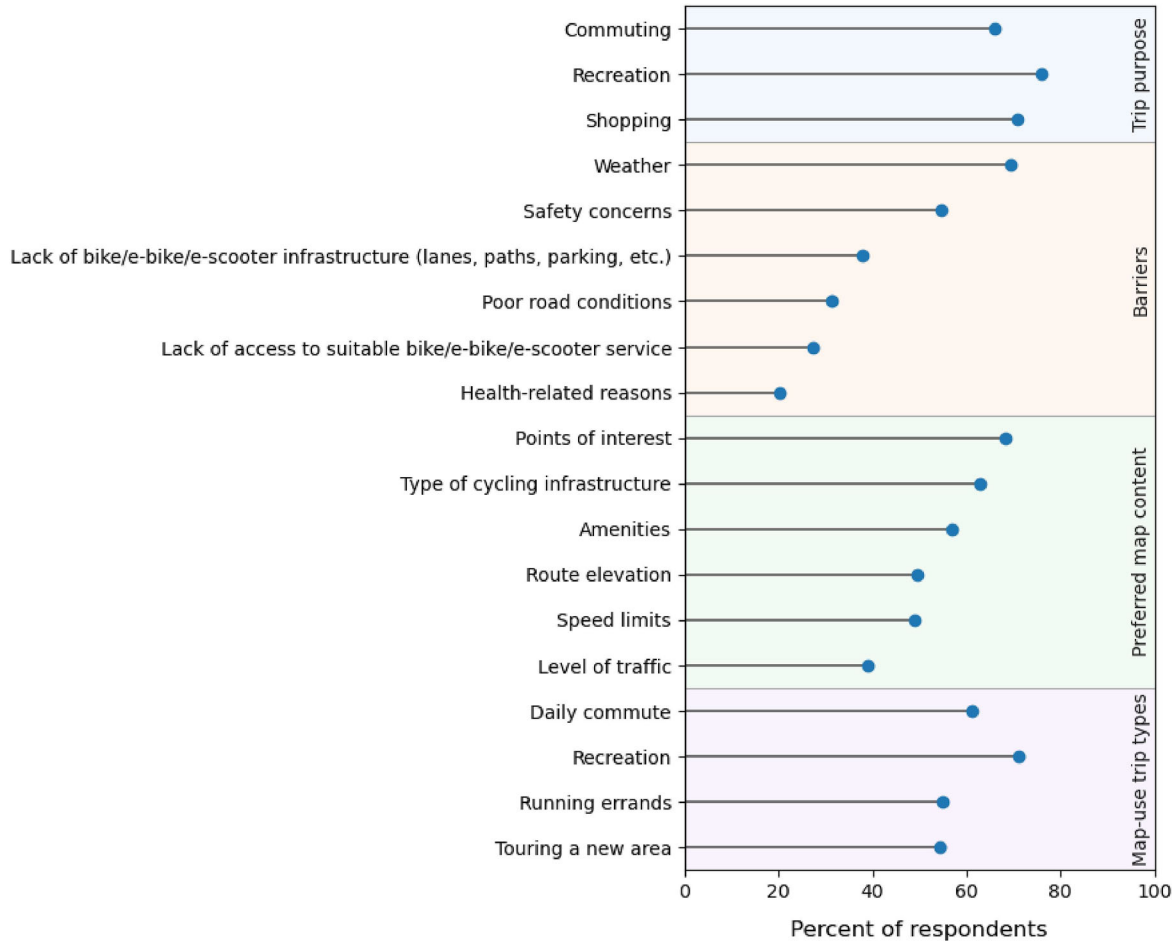


Fig. 6 Multi-response descriptive overview across trip purposes, reported barriers, desired map content, and intended map-use trip types

to map-use practices and access preferences than to riding frequency alone.

Model Results

The model separates two quantities that are easy to conflate because class membership and the ordered SMMI outcome are estimated jointly: what a rider type wants from a map, and how strongly map access is predicted to raise its stated use. The results below show that these do not coincide, a pattern that a split on any single observed variable would miss. We report the recovered rider types, their predicted SMMI, and the within-type associations behind it.

Four Rider Types Separated Regular Commuters, Fair-Weather Recreationists, Cautious Navigators, and Regular Leisure Riders

We selected the number of latent classes by comparing models from one to ten classes on the Bayesian Information Criterion (BIC) and the integrated classification likelihood BIC (ICL-BIC), retaining the four-class solution, which minimized both criteria while keeping every class large enough to interpret as a distinct rider type and avoiding the near-empty classes that appeared in larger specifications. The reported solution is the lowest ICL-BIC fit among random restarts.

The Bernoulli mixture component of the LCOLM recovered four latent classes corresponding to four rider types: *Regular Commuters* (35.9%), *Fair-Weather Recreationists* (21.2%), *Cautious Navigators* (8.8%), and *Regular Leisure Riders* (34.1%). These class shares describe the composition of the engaged-user sample and are not intended as population prevalences. The types differed systematically in map preferences, riding patterns, and reported constraints. We report the posterior class membership probabilities that define these types in Table 5.

Regular Commuters This type is defined by routine bicycle use and a strong commute orientation. Respondents in this type are characterized by commuting by bike, frequent use of route-mapping tools, and regular riding. They also show strong support for schematic maps and simpler maps while still valuing geographic accuracy, suggesting cyclists who

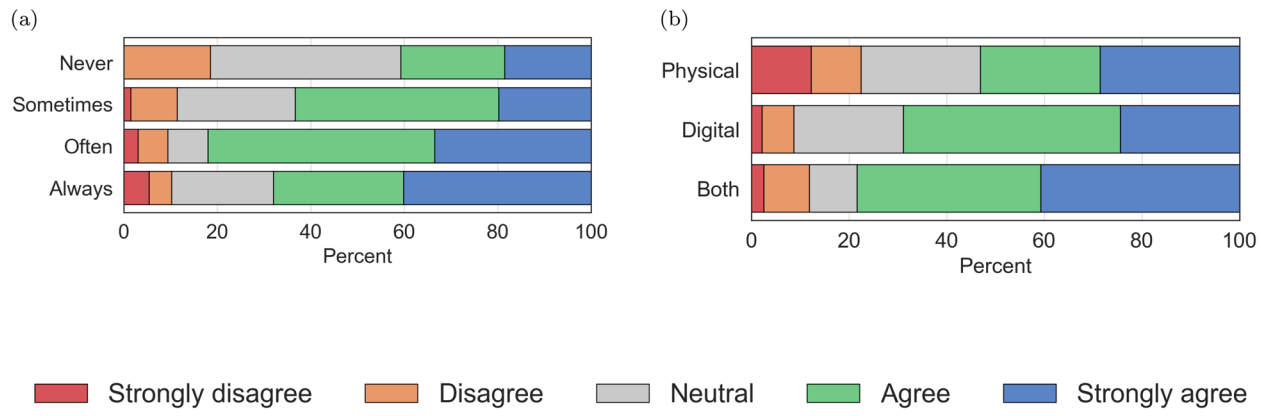


Fig. 7 SMMI by respondent context: **a** smartphone route-mapping frequency, and **b** preferred map access

Table 5 Summary of main class membership probabilities for the Bernoulli mixture component

Membership indicator	Regular Commuters	Fair-Weather Recreationists	Cautious Navigators	Regular Leisure Riders
Map preferences				
Prefers schematic maps	0.847	0.760	0.934	0.403
Prefers simpler maps	0.885	0.774	0.091	0.485
Prefers geographic accuracy	0.897	0.714	0.894	0.555
Use and navigation				
Frequently uses route mapping	0.887	0.312	0.887	0.465
Would use map for commuting	0.906	0.518	0.934	0.270
Commutes by bike	0.960	0.344	0.930	0.458
Would use map in new areas	0.534	0.459	0.872	0.556
Wants full network coverage	0.385	0.360	0.874	0.118
Wants traffic information	0.458	0.300	0.914	0.302
Wants infrastructure details	0.704	0.877	0.074	0.451
Wants physical map access	0.478	0.219	0.083	0.468
Riding patterns				
Regular rider	0.917	0.426	0.144	0.759
Rides for recreation	0.673	0.928	0.931	0.715
Bike-share user	0.836	0.708	0.906	0.573
Constraints and conditions				
Safety concerns	0.666	0.695	0.936	0.261
Infrastructure barrier	0.352	0.615	0.069	0.318
Weather barrier	0.766	0.936	0.930	0.411
Rides less in bad weather	0.741	0.893	0.926	0.314
Rides less in winter	0.451	0.737	0.888	0.579
Class share, π_c	0.359	0.212	0.088	0.341

Higher probabilities are shaded in blue and lower probabilities in red

already ride frequently and want maps that are easy to scan and practical for everyday trips. Because these riders already make frequent route decisions, an SMM overlaps directly with choices they are routinely making, the condition under which map access is most likely to register as useful.

Fair-Weather Recreationists This type combined recreational riding with a strong interest in infrastructure details and a high likelihood of reporting reduced riding in poor weather and winter conditions. It was less strongly associated with commuting and frequent route mapping than *Regular Commuters*, while being highly associated with recreational riding. This profile suggests a condition-sensitive type whose map needs are driven more by route quality and bikeability assessment than by routine navigation. Their sensitivity to conditions is what links this type to maps: a map that signals route quality speaks to the decision of whether a trip feels feasible at all.

Cautious Navigators This type was distinguished by strong safety concerns and a pronounced demand for network-level guidance. Respondents in this type showed high probabilities of wanting traffic information, full network coverage, and maps for riding in new areas, while also strongly favoring schematic maps and geographic accuracy. Unlike *Regular Commuters*, they were not characterized by regular riding, suggesting a type that relies on maps most when trips are unfamiliar or route conditions feel uncertain. The contrast between this strong stated demand and the type's infrequent regular riding and high safety concern creates a tension that is explored below, where the type that asks most for map information shows only a moderate and uncertain predicted response.

Regular Leisure Riders This type combined regular riding with a primarily recreational orientation and comparatively low demand for detailed map information. Respondents in this type were likely to ride regularly and for recreation, but were much less likely to use maps for commuting, request full network coverage, or want traffic information. They also showed weaker support for schematic maps, moderate use of route-mapping tools, and low levels of safety and infrastructure-related concerns, suggesting riders whose travel is less shaped by route uncertainty. With little route uncertainty to resolve, this type has the least for a map to add, which anticipates its low predicted SMMI.

These profiles show that the recovered types combine multiple dimensions of riding behavior, map use, trip purpose, and perceived constraints, with no single survey indicator defining the typology on its own.

Expected SMMI was Highest for Regular Commuters and Fair-Weather Recreationists

The four rider types also differed in how strongly they were expected to respond to schematic map access. Predicted SMMI declined across the types from *Regular Commuters* to *Regular Leisure Riders* (Figs. 8, 9, Table 6). Each type-level quantity carries a full posterior, so we report expected SMMI and the probability of a top-two response with 95% credible intervals and summarize between-type differences as posterior probabilities. All SMMI values reported in this section and in Table 6 are posterior expectations under the fitted model. Observed sample mean SMMI for each hard-assigned type is reported in Table 9.

The clearest contrast was between *Regular Commuters* and *Regular Leisure Riders*. The expected score declined from 3.366 (95% CrI 3.078, 3.612) to 2.174 (1.860, 2.470), and the probability of a top-two response declined from 0.910 (0.831, 0.959) to 0.424 (0.298, 0.546). The model places most of the expected inducement from schematic map access among commute-oriented and condition-sensitive riders, with weaker expected lift among leisure-oriented riders.

Regular Commuters had the Strongest Predicted Response Regular Commuters had the highest expected score and the greatest concentration of probability in the top-two outcome categories. For this type, schematic map access aligns with routine commuting and frequent route choice, where a clearer network presentation may directly support everyday mobility decisions.

Fair-Weather Recreationists were Similarly Receptive Fair-Weather Recreationists had the second highest predicted SMMI, with an expected score of 3.084 (2.742, 3.399) and a top-two probability of 0.808 (0.671, 0.903). Together with *Regular Commuters*, this type concentrated most probability mass in the upper part of the outcome scale, consistent with schematic map access being most relevant when riders are navigating routine travel or judging whether conditions feel manageable.

Cautious Navigators had a Moderate but Uncertain Predicted Response Cautious Navigators had an expected score of 2.887 (2.389, 3.304) and a top-two probability of 0.660 (0.503, 0.836), placing the type third, above *Regular Leisure Riders* but below the two most receptive types. This is the smallest type ($n = 53$), and its expected SMMI carries the widest credible interval of any type, so its position in the ranking is the least certain. This type reported the strongest stated demand for map information across the network-level indicators, yet the predicted association between map access and higher SMMI is moderate and imprecisely estimated.

Regular Leisure Riders showed the lowest predicted gains Regular Leisure Riders had the lowest predicted SMMI, with an expected score of 2.174 (1.860, 2.470) and a top-two probability of 0.424 (0.298, 0.546). The predicted distribution implies limited expected gains from schematic map access among riders whose travel is less commute-oriented and less dependent on detailed network guidance. In this type, riding tends to occur without heavy reliance on maps, which may reduce the marginal inducement associated with SMMs.

The posterior supports direct probabilistic comparisons between types. The probability that *Regular Commuters* have higher expected SMMI than *Regular Leisure Riders* is approximately one, and that they exceed *Cautious Navigators* and *Fair-Weather Recreationists* is 0.97 and 0.92, respectively. The probability that *Fair-Weather Recreationists* exceed *Cautious Navigators* is 0.75, and that *Cautious Navigators* exceed *Regular Leisure Riders* is 0.99. The two highest types and the single lowest type are therefore ordered with high posterior probability, whereas the position of *Cautious Navigators* relative to *Fair-Weather Recreationists* is less certain.

Overall, broad support for schematic maps at the sample level concealed substantial differences in where the strongest expected gains were concentrated. Expected inducement was highest among commute-oriented and condition-sensitive riders and lowest among *Regular Leisure Riders*, whose riding depends least on map-based navigation, while *Cautious Navigators*, the type reporting the strongest demand for map information, had a moderate response estimated with the greatest uncertainty.

A segmentation check confirms that these type-level differences are not reproduced by simple splits on regular riding, commuting, or safety concern. Those single-variable splits compress the observed SMMI gradient and mix respondents from multiple latent types (Table 9).

Higher SMMI Was Associated with Schematic Preference Across All Rider Types

Predicted SMMI varied across the four types, but the sources of that variation also differed within types. The type-specific ordered outcome model estimates which respondent characteristics and map preferences were associated with higher or lower SMMI within each type by allowing coefficients to vary across types. Positive coefficients indicate an association with higher SMMI categories within a type, and negative coefficients indicate an association with lower categories. We assess posterior credibility using a Region of Practical Equivalence (ROPE) (Makowski et al. 2019). The ROPE was defined on the ordered-logit coefficient scale as $[-0.18, 0.18]$, approximately equivalent to odds ratios between 0.835 and 1.197. For each coefficient, we report P_{out}, the posterior probability that the coefficient lies outside the ROPE in the direction of its posterior mean. A condensed summary of the type-specific coefficients, with ROPE-credible associations in bold, is reported in Table 7. Full posterior means, 95% credible intervals, P_{out}, and odds ratios are given in Tables 10 and 11, and Fig.10 visualizes the same coefficient estimates.

The coefficient estimates in Fig. 10 show common design-related correlates of higher SMMI across types. Preference for schematic maps had positive posterior means in all four rider types and was credible for *Regular Commuters*, *Fair-Weather Recreationists*, and *Regular Leisure Riders*. Design preferences beyond schematicity also mattered. The preference for simpler maps was most strongly and credibly associated with higher SMMI among *Fair-Weather Recreationists* and *Cautious Navigators*, while the preference for geographic accuracy was credible for *Regular Leisure Riders* and positive but less certain for *Regular Commuters* and *Cautious Navigators*. The pattern matches the descriptive results from earlier, which suggested that higher stated inducement was often associated with valuing both schematic clarity and geographic legibility. Figure 11 shows the posterior distributions of these three design-preference coefficients across types, which helps us determine the differing design priorities and their uncertainty. Schematic preference was consistently positive, whereas simpler-map and geographic accuracy preferences separated the types.

Regular Commuters Responded Most to Visible, Schematic, and Geographically Legible Maps

For *Regular Commuters*, higher SMMI was credibly associated with schematic map preference, regular riding, physical map access, and younger age. Frequent route mapping was negatively associated with higher SMMI. For this type, the association pattern is consistent with SMMs functioning as visible, easy-to-scan complements to routine travel.

Fair-Weather Recreationists Responded Most to Simple Maps that Clarified Route Quality For *Fair-Weather Recreationists*, the credible positive associations were preference for simpler maps, preference for schematic maps, and frequent route mapping. This is one of the clearest design-specific patterns in the model. For this type, higher SMMI appears to be tied to maps that make route quality easier to evaluate without overloading the rider with information.

Cautious Navigators Responded Most to Simplified Legible Maps For *Cautious Navigators*, higher SMMI was credibly associated with simpler maps, frequent route mapping, and physical map access, while no car access was strongly negatively associated with higher SMMI. This type was defined in the membership model by strong safety concerns and demand for network-level guidance, but those traits were not the strongest within-class predictors of higher SMMI. Within the type, the strongest associations point to legibility, orienting structure, and map availability. Respondents in this type reported higher SMMI when the map was simplified and readily available. The strong negative association for no car access also suggests that SMMs may be less inducive when broader mobility constraints are already substantial.

Regular Leisure Riders Showed Higher SMMI Mainly Among Younger Riders For *Regular Leisure Riders*, higher SMMI was credibly associated with schematic map preference, geographic accuracy, younger age, and no car access,

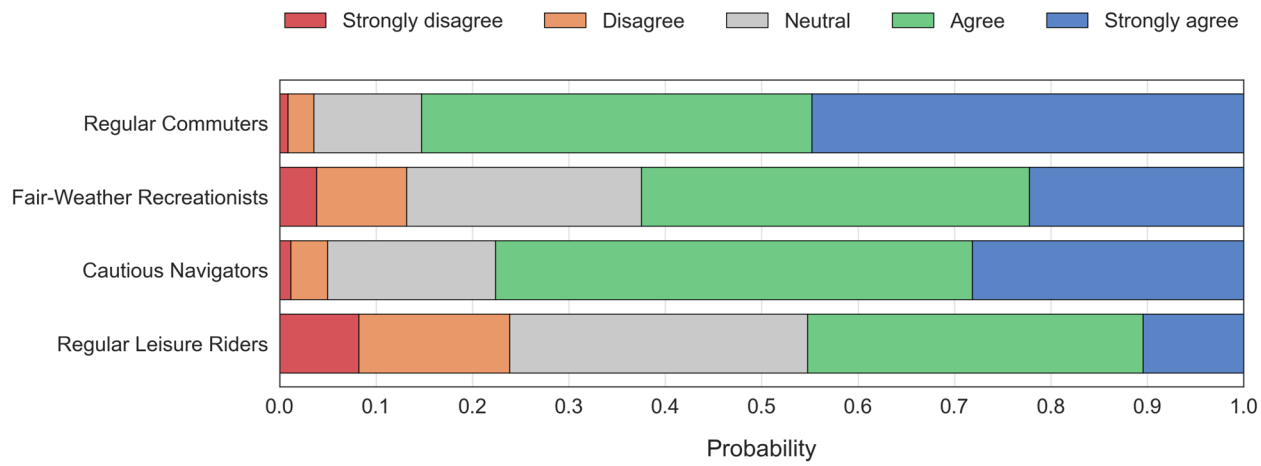


Fig. 8 Predicted SMMI by rider type

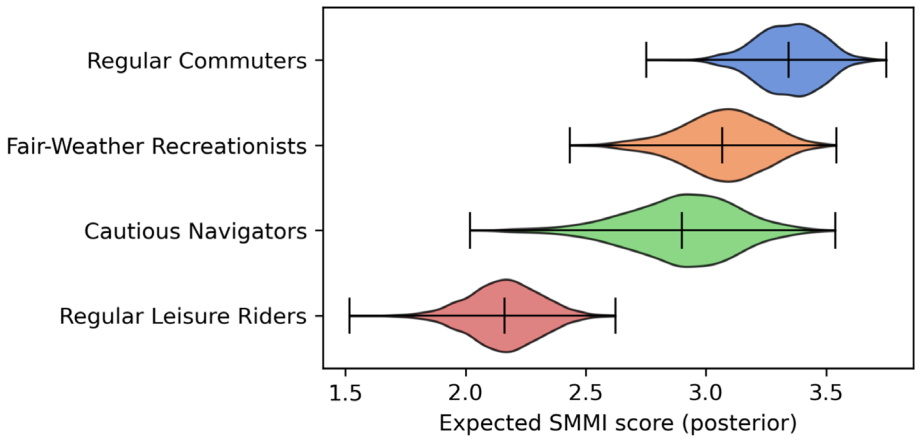


Fig. 9 Posterior distributions of type-level expected SMMI. Each violin is the full posterior of a type's expected SMMI score. The smallest type, *Cautious Navigators* ($n = 53$), has the widest interval

Table 6 Type sizes and type-level posterior expected SMMI in the selected four-class model

Type	Share (95% CrI)	Assigned respondents	Expected SMMI score (95% CrI)	Top two prob. (95% CrI)
Regular Commuters	0.359 (0.317, 0.403)	225	3.366 (3.078, 3.612)	0.910 (0.831, 0.959)
Fair-Weather Recreationists	0.212 (0.175, 0.250)	123	3.084 (2.742, 3.399)	0.808 (0.671, 0.903)
Cautious Navigators	0.088 (0.066, 0.114)	53	2.887 (2.389, 3.304)	0.660 (0.503, 0.836)
Regular Leisure Riders	0.341 (0.300, 0.382)	211	2.174 (1.860, 2.470)	0.424 (0.298, 0.546)

Expected SMMI score and top-two-category probability are posterior means with 95% credible intervals in parentheses. Observed sample mean SMMI for each type is reported in Table 9

while regular riding and bike-share use were negatively associated with higher SMMI. Within this type, the strongest positive associations were concentrated among younger respondents and those with fewer mobility alternatives. The negative associations for regular riding and bike-share use are consistent with lower inducement where riders are already well served by existing routines or micromobility services.

Discussion

Riders Prefer Spatial Orientation-Preserving Simplification

The strong simultaneous support for schematic design, simpler maps, and geographic accuracy suggests that users do not see these as competing priorities. This is consistent with evidence from transit and route mapping that abstraction improves legibility when it removes noise without removing structure (Avelar and Hurni 2006; Galvão et al. 2021). For micromobility, the implication is that a useful SMM

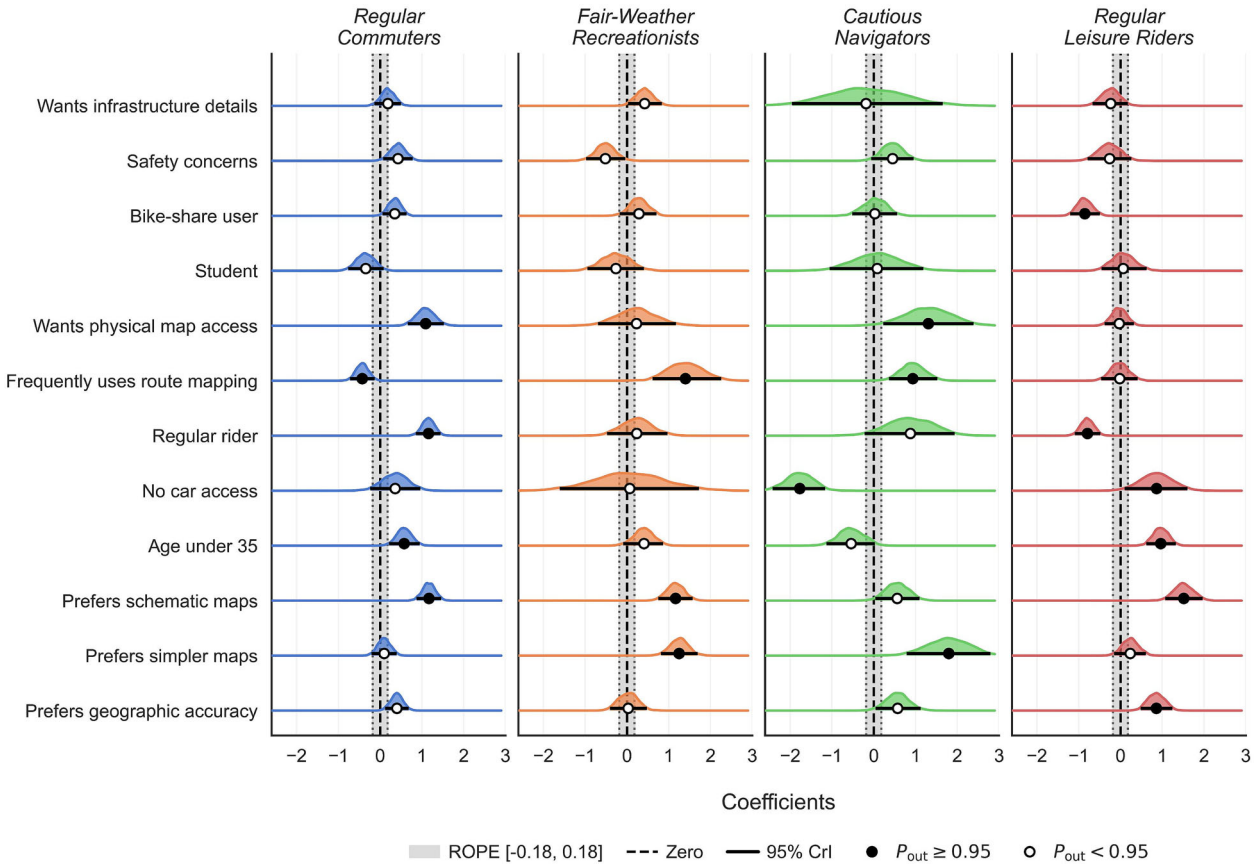


Fig. 10 Posterior distributions of type-specific ordered-logit coefficients for higher SMMI. Half violins show posterior coefficient distributions, darker regions show the 95% credible regions, and black horizontal segments show the 95% credible intervals. The gray vertical band marks the ROPE, $[-0.18, 0.18]$, and the dashed vertical line marks zero. Filled mean markers indicate coefficients with at least 95% posterior probability outside the ROPE in the direction of the posterior mean, while open markers indicate coefficients below that threshold

Table 7 Condensed type-specific ordered-logit coefficients (posterior means) for higher SMMI

Predictor	Regular Commuters	Fair-Weather Recreationists	Cautious Navigators	Regular Leisure Riders
Prefers geographic accuracy	0.398	0.028	0.569	**0.856**
Prefers simpler maps	0.094	**1.249**	**1.793**	0.233
Prefers schematic maps	**1.165**	**1.160**	0.562	**1.512**
Age under 35	**0.573**	0.403	−0.545	**0.963**
No car access	0.359	0.063	**−1.771**	**0.862**
Regular rider	**1.155**	0.234	0.876	**−0.794**
Frequently uses route mapping	**−0.429**	**1.401**	**0.934**	−0.023
Wants physical map access	**1.085**	0.225	**1.306**	−0.031
Student	−0.349	−0.265	0.081	0.064
Bike-share user	0.347	0.285	0.026	**−0.859**
Safety concerns	0.426	−0.516	0.449	−0.263
Wants infrastructure details	0.184	0.419	−0.185	−0.238

Bold entries denote coefficients with at least 95% posterior probability outside the ROPE in the direction of the posterior mean. Full posterior means with 95% credible intervals, P_{out}, and the corresponding odds ratios are reported in Tables 10 and 11

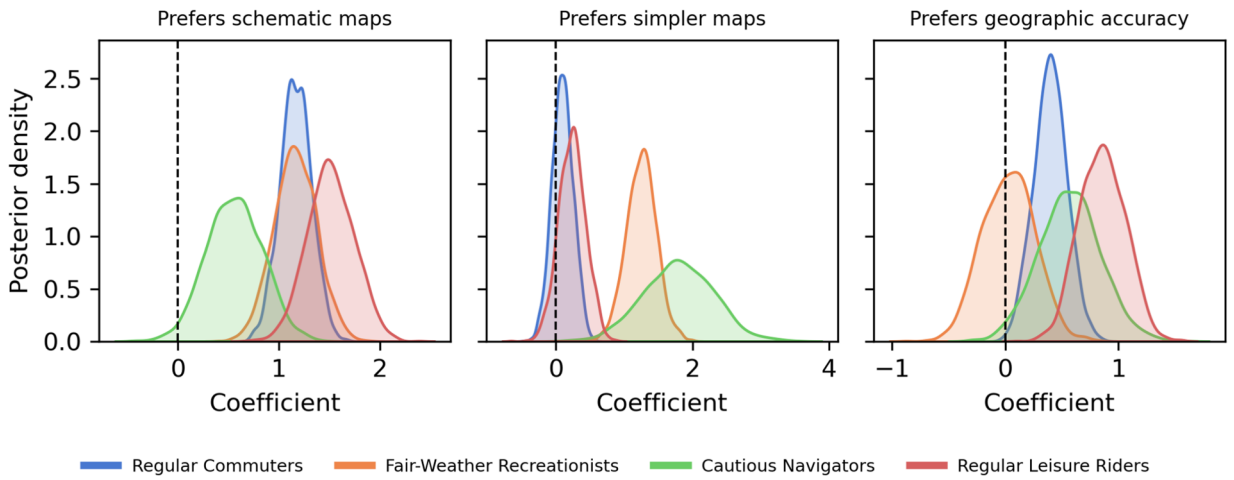


Fig. 11 Posterior distributions of the three map design preference coefficients for higher SMMI, by rider type. The dashed line marks zero

is not one that maximizes simplicity, but one that removes visual clutter while keeping the geographic cues riders need to stay oriented and make comfort-relevant decisions. The high demand for infrastructure type and points of interest reinforces this: respondents wanted maps that were easier to read but richer in decision-relevant content, not maps that sacrificed usable information for visual cleanliness. Recent route choice evidence suggests that some of the most decision-relevant attributes are not fully captured by network geometry alone. Meister et al. (2024) identify cycling infrastructure, traffic signals, lower-speed street environments, and gradient as key route quality attributes in Zurich, while Latvala et al. (2026) show that gradient is less constraining for e-bike users than for conventional cyclists. Gan et al. (2023) likewise suggest that uphill gradient is behaviorally more important than their lane- and speed-based road-condition proxies, although those proxies still indicate the importance of motorized traffic conditions. Although our survey did not isolate gradient as a separate desired map content item, this literature suggests that future SMMs would benefit from showing hilliness/gradient and motorized traffic exposure or traffic volume classes in simplified categorical form, alongside infrastructure type and points of interest.

The visiting–local SMMI gap showed that respondents were more likely to report higher SMMI when visiting an unfamiliar area than when navigating their local network, which is consistent with maps being most useful when route knowledge cannot be taken for granted. This points toward specific deployment settings where riders are likely to be navigating without prior familiarity. Cities investing in micromobility wayfinding infrastructure may see the strongest returns in these settings, where the informational gap between a confident local and a new rider is largest.

Expected Gains from Map Access Vary by Rider Type

Predicted SMMI varied substantially across rider types with clear implications for how SMMs should be framed as a policy tool. Broad support for schematic maps at the aggregate level does not mean that map access is equally effective for all riders. The four-class structure shows that the riders most likely to report higher SMMI are those for whom route information directly shapes a travel decision they are already trying to make.

For *Regular Commuters*, a clear and scannable network map supports a repeated, purposeful trip. This type already rides regularly and uses route-mapping tools often, so an SMM adds value as a legible, publicly posted representation of the network that reduces the cognitive effort of everyday route choice. The positive association with physical map access for this type is consistent with the value of posted maps at key decision points along commute corridors.

For *Fair-Weather Recreationists*, the mechanism is different. This type rides recreationally and is sensitive to conditions, such as weather, infrastructure quality, and perceived comfort, all of which shape whether a trip happens at all. Higher expected SMMI for this group aligns with maps that help riders assess whether a trip feels feasible under variable conditions, and the strong within-type associations with simpler and schematic maps support this interpretation, alongside this type's high probability of wanting infrastructure details in the membership model. For condition-sensitive riders, an SMM that clearly signals route type and facility quality may be what tips a trip from uncertain to planned.

Cautious Navigators reported the strongest demand for map information across the network-level indicators, including traffic conditions, full network coverage, and maps for new areas, but their predicted SMMI was only moderate and was the most uncertain of any type, reflecting the small size

of this class. The evidence that map access alone is associated with higher use is therefore weaker and less certain for this group than for commute-oriented riders. This is consistent with a broader finding in active travel research that information provision has limited effect when the underlying infrastructure or perceived safety environment is inadequate (Winters and Teschke 2010; Teschke et al. 2012). For riders constrained by safety concerns and traffic exposure, infrastructure investment and traffic management are likely preconditions for map-based interventions to be fully effective, so SMMs should complement rather than substitute for those investments.

Regular Leisure Riders showed the lowest predicted gains, for a different reason. This type rides regularly but recreationally, with low map dependence and few reported barriers. Riding already happens without structured navigation support, which reduces the marginal value of an SMM. This does not mean the map is useless for this group, since the within-type coefficient results show that younger riders and those without car access did show higher SMMI. The aggregate effect is modest because most riders in this type do not face the navigational uncertainty that maps are best positioned to address.

Type-Specific Associations Inform Differentiated Map Design

Across all four types, preference for schematic maps had a positive posterior mean, and the association was credible for three of the four types. This result supports schematic design as a broadly relevant map feature, while also showing that the strength of posterior support differs by rider type. The type-specific variation, however, shows that the features that matter most differ by rider type, which has direct implications for map design prioritization.

For *Regular Leisure Riders*, geographic accuracy was among the strongest positive predictors of higher SMMI, while for *Regular Commuters* and *Cautious Navigators*, it was positive but below the credibility threshold. For *Fair-Weather Recreationists* and *Cautious Navigators*, simpler maps were credibly associated with higher SMMI. This suggests that the informational priority for map design is not the same across groups: condition-sensitive and safety-concerned riders benefit most from reduced visual complexity, while leisure riders place more weight on spatial legibility and commuters show strongest support for schematic, posted, easy-to-scan maps.

Rider heterogeneity in wayfinding and infrastructure preferences is well established in the literature (Dill and McNeil 2016; Clark et al. 2021; Aldred et al. 2017), and this study provides direct evidence that those differences extend to how riders respond to schematic maps. The latent class structure connects established typologies of cycling behavior to map-specific outcomes for the first time, offering a more precise basis for targeting SMM design and deployment than demographic or usage-frequency variables alone.

Policy and Practical Implications

The findings point to a set of practical recommendations for cities planning where, for whom, and how to deploy SMMs. These follow from the stated preferences and predicted responses reported above and are meant to connect the behavioral results to concrete planning choices.

The clearest signal about where to deploy first comes from the visiting–local SMMI gap. Respondents reported higher SMMI when visiting an unfamiliar area (79.7%) than in their local context (70.6%), and the paired difference was statistically significant. This favors settings where riders are least likely to already know the network: downtown cores, transit hubs and stations, university campuses, visitor and tourist districts, trailheads, and bike-share docking areas. These are also the places where a posted map reaches a rider at the moment a route decision is being made. Cities with limited budgets should prioritize these high-unfamiliarity, high-traffic locations before a broader rollout.

The rider types most likely to benefit are commute-oriented and condition-sensitive riders. Predicted SMMI was highest for *Regular Commuters* (expected score 3.366, top-two-category probability 0.910) and *Fair-Weather Recreationists* (3.084, 0.808), moderate but more uncertain for *Cautious Navigators* (2.887, 0.660), and lowest for *Regular Leisure Riders* (2.174, 0.424). The practical reading is that map access does most work for riders who are already near a travel decision that better route information can move, either a repeated commute trip or a conditional recreational trip. It does least for riders who either do not rely on maps or face barriers a map cannot remove.

Map design should be tuned to context and rider type rather than fixed. Schematic preference was positive across all four types and credible for three of them, so a schematic base is a reasonable default. The balance beyond that should shift with the setting. Along commute corridors, where *Regular Commuters* are a key target, maps should emphasize schematic clarity and posted visibility. For recreational and cautious riders, where simpler maps were the stronger credible correlate, maps should lead with a decluttered layout that foregrounds route type and facility quality. For *Regular Leisure Riders*, geographic accuracy was credible, suggesting that spatial legibility remains important where riders are less dependent on detailed network guidance. Across all settings, maps should show the content riders asked for most, namely points of interest (68.3%), infrastructure type (62.9%), and amenities (57.0%), since these match the barriers riders reported.

SMMs should complement infrastructure investment, not substitute for it. The clearest evidence is the *Cautious Navigators* result. This type reported the strongest demand for map information across the network-level indicators, including traffic information, full network coverage, and maps for new areas, yet its predicted SMMI was only moderate and was the most uncertain of any type. For riders whose travel is constrained by safety concerns and traffic exposure, the binding constraint is the road environment, not the availability of information, and a map cannot make an uncomfortable route comfortable. For these riders and the corridors they use, map deployment should follow or accompany infrastructure improvements such as protected facilities and low-stress routing. Maps are most effective where a usable route already exists but is hard to find or to judge.

Finally, digital and physical deployment serve different priorities. Most respondents preferred digital access (60.3%), but those who preferred both digital and physical access reported higher SMMI than those preferring either alone, and posted physical access was a strong credible within-type predictor of higher SMMI for *Regular Commuters* (odds ratio 2.960, $P_{\text{out}} = 1.000$) and *Cautious Navigators* (odds ratio 3.693, $P_{\text{out}} = 0.978$) while being close to neutral for the other two types. A digital base map provides reach and easy updating, but a digital-only strategy would under-serve exactly the groups that respond to posted maps. The stronger approach is a digital map paired with targeted physical installations at the high-decision points identified above: corridor decision points for commuters and area entry points for cautious and unfamiliar riders.

Limitations

The primary outcome is self-reported SMMI, which is a stated increase in the likelihood of using a bike, e-bike, or e-scooter when an SMM is available. This reflects perceived usefulness and anticipated behavior, not observed change. Whether exposure to a real SMM translates into actual route choice or mode shift is a question this study cannot answer. Behavioral validation through field experiments or natural experiments around SMM deployment is an important next step. A related limitation is that the survey instrument did not separately isolate all route choice attributes emphasized in the recent literature, especially gradient and motorized traffic exposure. Our traffic information item partially speaks to this domain, but future survey instruments and map design experiments should test those attributes directly.

The sample was also more active and map-engaged than the general population. High rates of frequent riding, bikeshare use, and smartphone route mapping make the study well suited for identifying heterogeneity among current and near-current users, but the findings may not generalize to populations with very low prior engagement with micromobility. The *Cautious Navigators* class, which comprised 8.8% of the sample, may be larger and more heterogeneous in a general-population sample, and the gap between their stated map demand and their predicted SMMI might look different there.

Conclusion

This study examined what micromobility users want from schematic micromobility maps and whether access to such maps is associated with a higher SMMI. Three findings stand out. First, respondents did not treat schematic design and geographic legibility as competing goals, as support was high for all three preference dimensions simultaneously, indicating that users want maps that simplify the network without removing the spatial structure needed for orientation. Second, the visiting–local SMMI gap was consistent and statistically significant, suggesting that SMMs are especially useful in unfamiliar settings and pointing toward visitor-oriented and transit-adjacent locations as priority deployment contexts. Third, the effect of map access was not uniform across rider types. Predicted SMMI was highest among *Regular Commuters* and *Fair-Weather Recreationists* and lowest among *Regular Leisure Riders*. *Cautious Navigators*, the type with the strongest stated demand for map information, showed a moderate predicted response estimated with the greatest uncertainty.

The type-level results carry a clear policy implication. For riders whose travel is constrained by safety concerns and traffic exposure, the association between map access and greater micromobility use is weaker and less certain than for commute-oriented riders, so improving infrastructure conditions is likely a precondition for informational interventions to become fully effective for this group. For riders who are already traveling or near the decision threshold, a well-designed SMM, schematic, geographically legible, and condition-informative, can provide the navigational support that shifts a trip from uncertain to possible. Cities promoting micromobility as a sustainable urban transport option should treat SMMs as a complement to infrastructure investment, targeted toward deployment contexts and rider groups where the informational gap is the binding constraint. Future research should test these relationships using observed behavior, examining how real SMM deployment affects route choice, trip frequency, and mode uptake across different urban contexts.

Appendix A. Survey Instrument

The following reproduces all questions from the survey as administered via Qualtrics (May 29–August 31, 2025).

Respondents first completed the consent form (Q1), then viewed the schematic map example (Q2, reproduced as Fig. 2 in Sect. Survey Instrument and Analytic Variables), and then answered Q3–Q23. The study was approved by the University of Massachusetts Amherst IRB (Protocol #5917).

Q1. Informed Consent. Participants were informed of the study title ("Can Schematic Bicycle Maps Reduce Greenhouse Gas Emissions?"), purpose, procedures, estimated completion time (≈10 min), compensation ($7 gift card), risks (minimal. Confidentiality risk mitigated by not collecting names or email addresses in the survey), and the voluntary nature of participation. IP addresses were collected solely to screen duplicate submissions, while email addresses for compensation were collected through a separate unlinked form. Consent was obtained by selecting "I Agree" before proceeding.

Q2. Schematic map example. Before the map preference questions, respondents were shown the prompt: *"Schematic maps simplify complex networks by focusing on clarity, not geographic accuracy. Below is a metro network shown in both geographic and schematic formats."* The accompanying side-by-side figure of the Boston MBTA network is reproduced as Fig. 2.

Demographics (Q3–Q7)

Q3. What is your age range?

- 18 to 24 years
- 25 to 34 years
- 35 to 44 years
- 45 to 54 years
- 55 to 64 years
- 65 years or greater
- Prefer not to answer

Q4. What is your gender identity?

- Female
- Male
- Non-binary
- Prefer not to answer

Q5. Are you a student?

- Yes
- No
- Prefer not to answer

Q6. What is the size of your household?

- 1
- 2
- 3
- 4+
- Prefer not to answer

Q7. How many cars do you have available in your household?

- 0
- 1
- 2
- 3+
- Prefer not to answer

Bike and E-Scooter Ownership/Usage (Q8–Q13)

Q8. How often do you use a bike/e-bike/e-scooter?

- Always
- Often
- Sometimes
- Never

Q9. What do you use a bike/e-bike/e-scooter for? *(Select all that apply.)*

- Commuting
- Recreation
- Shopping
- Other:

Q10. How many bikes/e-bikes/e-scooters do you have available in your household?

- 0
- 1
- 2
- 3+
- Prefer not to answer

Q11. Do you use a bike/e-bike/e-scooter sharing service?

- Yes
- No

Q12. What are some barriers that prevent you from using a bike/e-bike/e-scooter more often? *(Select all that apply.)*

- Safety concerns
- Lack of bike/e-bike/e-scooter infrastructure (lanes, paths, parking, etc.)
- Lack of access to suitable bike/e-bike/e-scooter service (cargo needs, child seat, etc.)

- Poor road conditions
- Health-related reasons
- Weather
- I don't know how to bike
- None of the above
- Other:

Q13. How does the season or weather affect your bike/e-bike/e-scooter usage? *(Select all that apply.)*

- No change
- I ride less in the winter
- I ride less in the summer
- I ride less in bad weather

Map Preferences and Attitudes (Q14–Q23)

Q14. How often do you use a smartphone to map a route when using a bike/e-bike/e-scooter?

- Always
- Often
- Sometimes
- Never
- I don't have access to a smartphone

For Q15–Q19, please indicate your level of agreement (Strongly disagree/Disagree/Neutral/Agree/Strongly agree).

Q15. A bike/e-bike/e-scooter map should be as geographically accurate as possible (e.g., showing exact road layouts and distances between locations).

Q16. I would prefer a bike/e-bike/e-scooter map that is simple to one with complete information (e.g., every route, stop, points of interest).

Q17. I would prefer a schematic [metro/subway-style] map of bike/e-bike/e-scooter routes to a geographically accurate one.

Q18. I would be more likely to use a bike/e-bike/e-scooter if a schematic [metro/subway-style] map of relevant routes were posted at various locations around the area I live.

Q19. I would be more likely to use a bike/e-bike/e-scooter if a schematic [metro/subway-style] map of relevant routes were available in an area I was visiting.

Q20. Which of the following aspects are important to display on a schematic [metro/subway-style] map of bike/e-bike/e-scooter routes? *(Select all that apply.)*

- Type of cycling infrastructure (painted bike lanes, protected bike lanes, bike paths)
- Route elevation (steepness)
- Amenities (bike parking facilities, showers, etc.)
- Points of interest (transit stops, bike shops, bike-sharing stations, malls, etc.)
- Speed limits
- Level of traffic
- Entire road network
- Other:

Q21. What trip types would you use a bike/e-bike/e-scooter map for? *(Select all that apply.)*

- Daily commute
- Recreation
- Running errands
- Touring a new area
- Other:

Q22. Where would you prefer to access bike/e-bike/e-scooter maps?

- Digital maps (phone, GPS apps)
- Physical maps (posted at locations)
- Both

Q23. Is there any other information that you would like to see on a schematic [metro/subway-style] map of bike/e-bike/e-scooter routes? *(Open text response.)*

Appendix B. Survey Data Cleaning and Bot Removal

The analytic sample was secured using the multi-filter bot-detection pipeline developed and validated in our companion study (Ruger et al. 2026), to which we refer the reader for full filter definitions, thresholds, sensitivity and ablation analyses, and validation against blind expert review and a supervised classifier. Table 8 reports the per-filter reduction from the 12,020 raw submissions to the 620 valid responses retained by the pipeline, applied in pipeline order. The analytic sample used in this paper ($N = 612$) comprises the valid responses with complete data on all variables entering the latent class model.

Appendix C. Segmentation Check

To assess whether the four latent rider types could be recovered from simpler observed variable splits, we compared the selected four-class assignment with partitions based on regular riding, commuting by bike, and safety concern. These variables correspond to the most intuitive manual segmentations suggested by the class labels. The comparison

summarizes the adjusted Rand index between each binary split and the four-class assignment, along with observed mean SMMI within each split (Table 9).

Appendix D. Class-Specific Coefficient Estimates

We report the class-specific ordered-logit estimates for higher SMMI. Table 10 presents the coefficient estimates, and Table 11 reports the corresponding odds ratios.

Across both tables, intervals in parentheses denote 95% credible intervals. ROPE was defined on the ordered-logit coefficient scale as $[-0.18, 0.18]$, approximately equivalent to odds ratios between 0.835 and 1.197. We report P_{out}, the posterior probability that the coefficient lies outside the ROPE in the direction of its posterior mean. Bold entries indicate coefficients with at least 95% posterior probability outside the ROPE in the direction of the posterior mean.

Table 8 Per-stage reduction of the survey sample under the multi-filter bot-detection pipeline of Ruger et al. (2026)

Category	Filter	Removed	Cumulative %
Platform-generated risk signals	Low reCAPTCHA score	6082	50.60
	High fraud score	2658	72.71
	Response ambiguity	42	73.06
Identity	Duplicate identity	859	80.21
Interaction patterns	Zero clicks	568	84.94
	Duplicate temporal pattern	46	85.32
	Extreme page duration	1056	94.11
	Extreme survey duration	72	94.71
Device consistency	Invalid resolution	3	94.73
	Software incompatibility	12	94.83
	User agent inconsistency	2	94.84
Valid responses retained by pipeline		620	
Analytic sample (complete cases for modeling)		612	

"Removed" is the number of submissions excluded at each stage in pipeline order; "Cumulative %" is the share of the original 12,020 submissions removed through that stage

Table 9 Comparison between the latent four-class typology and simple single-variable segmentations

Single-variable split	ARI vs 4-class	Mean SMMI (0–4) Split = 1	Split = 0
Regular rider	0.14	2.90	2.78
Commutes by bike	0.20	3.02	2.57
Safety concerns	0.10	3.05	2.65
Four latent types (reference), observed sample mean SMMI:			
Regular Commuters ($n = 225$)	–	3.40	
Fair-Weather Recreationists ($n = 123$)	–	3.14	
Cautious Navigators ($n = 53$)	–	2.96	
Regular Leisure Riders ($n = 211$)	–	2.12	

ARI is the adjusted Rand index between each binary split and the four-class assignment. Mean SMMI is the observed sample mean of the outcome on the 0–4 scale. The bottom rows report observed sample mean SMMI by hard-assigned latent type for reference. The corresponding posterior expected SMMI for each type is reported in Table 6

Table 10 Class-specific ordered-logit coefficients for higher SMMI with ROPE-based posterior credibility

Predictor	Regular Commuters			Fair-Weather Recreationists			Cautious Navigators			Regular Leisure Riders		
	Coef.	95% CrI	P_{out}	Coef.	95% CrI	P_{out}	Coef.	95% CrI	P_{out}	Coef.	95% CrI	P_{out}
Prefers geographic accuracy	0.398	(0.113, 0.685)	0.926	0.028	(−0.410, 0.473)	0.259	0.569	(0.039, 1.124)	0.921	**0.856**	**(0.477, 1.239)**	**1.000**
Prefers simpler maps	0.094	(−0.212, 0.394)	0.282	**1.249**	**(0.813, 1.694)**	**1.000**	**1.793**	**(0.785, 2.791)**	**0.999**	0.233	(−0.159, 0.611)	0.609
Prefers schematic maps	**1.165**	**(0.868, 1.461)**	**1.000**	**1.160**	**(0.749, 1.571)**	**1.000**	0.562	(0.036, 1.098)	0.920	**1.512**	**(1.064, 1.965)**	**1.000**
Age under 35	**0.573**	**(0.207, 0.944)**	**0.983**	0.403	(−0.092, 0.861)	0.833	−0.545	(−1.136, 0.023)	0.877	**0.963**	**(0.613, 1.324)**	**1.000**
No car access	0.359	(−0.242, 0.963)	0.713	0.063	(−1.612, 1.723)	0.445	**−1.771**	**(−2.424, −1.166)**	**1.000**	**0.862**	**(0.096, 1.604)**	**0.960**
Regular rider	**1.155**	**(0.852, 1.443)**	**1.000**	0.234	(−0.483, 0.971)	0.562	0.876	(−0.221, 1.936)	0.895	**−0.794**	**(−1.099, −0.484)**	**1.000**
Frequently uses route mapping	**−0.429**	**(−0.728, −0.133)**	**0.955**	**1.401**	**(0.611, 2.253)**	**0.996**	**0.934**	**(0.362, 1.521)**	**0.994**	−0.023	(−0.466, 0.412)	0.233
Wants physical map access	**1.085**	**(0.657, 1.523)**	**1.000**	0.225	(−0.699, 1.175)	0.535	**1.306**	**(0.222, 2.388)**	**0.978**	−0.031	(−0.382, 0.321)	0.202
Student	−0.349	(−0.769, 0.084)	0.779	−0.265	(−0.950, 0.408)	0.603	0.081	(−1.057, 1.186)	0.435	0.064	(−0.459, 0.623)	0.340
Bike-share user	0.347	(0.054, 0.630)	0.865	0.285	(−0.175, 0.707)	0.679	0.026	(−0.519, 0.560)	0.307	**−0.859**	**(−1.209, −0.492)**	**1.000**
Safety concerns	0.426	(0.068, 0.778)	0.910	−0.516	(−0.981, −0.043)	0.919	0.449	(−0.063, 0.953)	0.857	−0.263	(−0.791, 0.255)	0.625
Wants infrastructure details	0.184	(−0.143, 0.501)	0.504	0.419	(0.022, 0.836)	0.867	−0.185	(−1.959, 1.651)	0.510	−0.238	(−0.674, 0.174)	0.599

Posterior means are reported with 95% credible intervals. Bold entries denote coefficients with at least 95% posterior probability outside the ROPE in the direction of the posterior mean

Table 11 Class-specific odds ratios for higher SMMI with ROPE-based posterior credibility

Predictor	Regular Commuters			Fair-Weather Recreationists			Cautious Navigators			Regular Leisure Riders		
	OR	95% CrI	P_{out}	OR	95% CrI	P_{out}	OR	95% CrI	P_{out}	OR	95% CrI	P_{out}
Prefers geographic accuracy	1.488	(1.120, 1.983)	0.926	1.029	(0.663, 1.605)	0.259	1.767	(1.039, 3.078)	0.921	**2.354**	**(1.611, 3.453)**	**1.000**
Prefers simpler maps	1.099	(0.809, 1.482)	0.282	**3.486**	**(2.254, 5.442)**	**1.000**	**6.010**	**(2.191, 16.296)**	**0.999**	1.262	(0.853, 1.842)	0.609
Prefers schematic maps	**3.207**	**(2.383, 4.308)**	**1.000**	**3.191**	**(2.115, 4.812)**	**1.000**	1.754	(1.037, 2.998)	0.920	**4.537**	**(2.899, 7.137)**	**1.000**
Age under 35	**1.774**	**(1.230, 2.571)**	**0.983**	1.497	(0.912, 2.366)	0.833	0.580	(0.321, 1.023)	0.877	**2.620**	**(1.847, 3.757)**	**1.000**
No car access	1.431	(0.785, 2.620)	0.713	1.065	(0.200, 5.602)	0.445	**0.170**	**(0.089, 0.312)**	**1.000**	**2.369**	**(1.101, 4.972)**	**0.960**
Regular rider	**3.173**	**(2.344, 4.234)**	**1.000**	1.263	(0.617, 2.640)	0.562	2.402	(0.802, 6.931)	0.895	**0.452**	**(0.333, 0.616)**	**1.000**
Frequently uses route mapping	**0.651**	**(0.483, 0.875)**	**0.955**	**4.060**	**(1.843, 9.515)**	**0.996**	**2.545**	**(1.436, 4.578)**	**0.994**	0.977	(0.627, 1.509)	0.233
Wants physical map access	**2.960**	**(1.928, 4.586)**	**1.000**	1.253	(0.497, 3.239)	0.535	**3.693**	**(1.248, 10.891)**	**0.978**	0.970	(0.683, 1.378)	0.202
Student	0.706	(0.463, 1.088)	0.779	0.767	(0.387, 1.503)	0.603	1.084	(0.348, 3.275)	0.435	1.067	(0.632, 1.864)	0.340
Bike-share user	1.415	(1.055, 1.877)	0.865	1.329	(0.840, 2.027)	0.679	1.027	(0.595, 1.751)	0.307	**0.424**	**(0.298, 0.612)**	**1.000**
Safety concerns	1.532	(1.070, 2.178)	0.910	0.597	(0.375, 0.958)	0.919	1.566	(0.939, 2.593)	0.857	0.769	(0.453, 1.290)	0.625
Wants infrastructure details	1.203	(0.867, 1.651)	0.504	1.521	(1.023, 2.308)	0.867	0.831	(0.141, 5.214)	0.510	0.788	(0.509, 1.190)	0.599

Odds ratios are exponentiated coefficient posterior means, with exponentiated 95% credible intervals. Bold entries denote coefficients with at least 95% posterior probability outside the ROPE in the direction of the posterior mean

Author Contributions M.A. contributed to the methodology, implemented the software, performed the formal analysis, curated the data, created all figures and tables, and wrote the original draft. A.R. contributed to the formal analysis and investigation and co-wrote portions of the original draft. E.C. conceptualized the study, secured funding, supervised the research, and reviewed and edited the manuscript. J.O. conceptualized the study, developed the methodology, secured funding, supervised the research, and reviewed and edited the manuscript. All the authors reviewed the manuscript.

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Data Availability The survey datasets analyzed during the current study are not publicly available due to privacy restrictions regarding human participants.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Ethical Approval This study was approved by the Institutional Review Board at the University of Massachusetts Amherst (Protocol #5917). All survey participants provided informed consent prior to participation.

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