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Agent-Based Psychometric Route Optimization: Personality-Driven Pedestrian Navigation and Infrastructure Design

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ABSTRACT

Current pedestrian routing assumes all pedestrians are identical and optimizes a single objective such as journey time, despite 6 decades of evidence showing personality consistently influences route preference. This paper develops a route, an agent-based framework that maps Big-Five-plus-sensation-seeking profiles to eight route attributes through a multinomial logit (MNL) cost function governed by an 8×6 personality, attribute interaction matrix (γ). The framework integrates a Mesa 3.x simulation on the Boğaziçi University campus map (740 nodes, 1,892 edges, SRTM elevation 4–135 m), a five-layer multi-modal pathfinder governed by a personality–mode matrix (δ), and a p-median facility-location optimiser that converts personality-segmented demand into infrastructure placement. Three converging lines of evidence support the approach. A 2,000-agent simulation produced significant alignment improvements on all nine pre-registered tests at $p < .001$ (Reserved archetype Cohen's $d = 1.563$), and was robust to terrain. A real Phase 1 screening survey ($n = 26$, 19 eligible) confirmed 16 of 23 hypothesised δ sign directions (70 %, binomial $p = .047$). A synthetic pipeline validation produced large subjective-measure effects (satisfaction $d = 1.169$, commercial viability $d = 1.445$) while objective deviation stayed flat. A multi-modal extension cut travel time by 43 %; the optimiser recommended 23 scooter docks, saving 2,397 person-hours per day at Gini = 0.007. Personality matters for routing, as does the technology that underlies it.

1. Introduction

Urban pedestrian navigation has converged on a single convention where every walker is treated as interchangeable, and routes are optimised for one objective, usually the shortest time or distance [1]. This one-size-fits-all assumption is convenient and computationally trivial, yet it stands at odds with six decades of evidence that travel behaviour is shaped not only by spatial constraints but also by stable psychological dispositions. Personality systematically predicts route preference. Anxious individuals avoid crowds and poorly lit stretches, open individuals detour for scenery, and conscientious individuals trade scenery for reliability. No prior framework, however, translates these well-documented dispositions into operational routing weights through a formal choice model. This

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paper develops such a framework, namely Rota, and reports converging evidence, from a 2,000-agent simulation, a real screening survey, and a synthetic pipeline validation, that personality matters not only for individual route recommendation but also for the physical infrastructure that routing depends on.

1.1 Personality and Travel Behaviour

Research in travel-behaviour psychology has long recognised the role of personality in shaping mobility decisions. Ory and Mokhtarian [2] demonstrated that personality traits predict travel-related attitudes and mode choice after controlling for sociodemographic variables, explaining 8–15 % of variance in travel attitudes. Anable [3] identified six psychographic commuter segments whose distinct modal preferences could not be explained by infrastructure or cost alone. In the pedestrian domain specifically, walkers routinely deviate from time-optimal paths for reasons of aesthetics, perceived safety, terrain, and novelty seeking [4, 5]. These deviations are systematic, not random, and they correlate with measurable personality traits. Algorithmic scenic routing improves user satisfaction over shortest-path alternatives, yet such personalisation has remained reactive, requiring observed behavioural history before it can act.

The Five-Factor Model [6], namely Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism (OCEAN), supplies the dominant cross-culturally validated taxonomy of individual differences [7]. Augmented with sensation seeking, a construct closely tied to risk tolerance and novelty preference [8], the resulting six-trait vector offers a compact yet expressive representation of the dimensions most relevant to route choice. Neuroticism is associated with avoidance of crowded space and sensitivity to poor lighting [9]. Extraversion and sensation seeking predict adventurous, risk-tolerant mobility [10]. Agreeableness correlates with willingness to accept longer routes for collective benefit such as reduced emissions [11].

1.2 From Routing to Physical Design

The motivation of this work extends beyond individual route recommendation to campus infrastructure design. Standard planning relies on aggregate demand. If a significant fraction of those travellers are anxiety-prone individuals who will never use an exposed bike lane on a steep hillside, the investment serves fewer people than projected. Conversely, if sensation-seekers cluster in specific zones, scooter docks placed there will see higher utilisation. A framework producing personality-segmented demand answers a question aggregate models cannot: not just where people move, but who moves and what infrastructure they will actually use.

1.3 Research Gaps and Questions

The literature reveals a convergence of mature but disconnected traditions, namely transport psychology, discrete choice theory, agent-based modelling and personalised navigation, none of which has been unified. Four gaps structure this work. (G1) No prior framework translates Big Five traits into pedestrian routing weights through a formal choice model. (G2) No pedestrian routing system has been validated by both large-scale simulation and field evidence under one evaluation protocol. (G3) Existing pedestrian routing is single-modal, neglecting the campus ecosystem of walking, micro-mobility, and shuttle. (G4) No framework translates personality-driven mobility into infrastructure-design recommendations.

Two research questions follow. RQ1. Can personality traits, measured by a validated short-form instrument, be mapped to pedestrian routing weights through a multinomial logit (MNL) cost function that produces measurably better outcomes, in simulation and in user experience, than one-size-fits-all routing? RQ2. Can personality-segmented demand inform where mobility infrastructure (bike racks, scooter docks, shuttle stops, lighting) should be placed to better serve the actual behavioural composition of a campus population? The significant gap addressed here is the simultaneous absence of (i) a formal personality-to-routing coefficient matrix, (ii) a validated end-to-end empirical pipeline for it, and (iii) a path from the resulting demand to physical infrastructure design.

2. Methodology

This section develops the apparatus in six steps: the MNL cost function and the personality–attribute γ matrix (2.1), the campus digital twin (2.2), the psychometric instruments and archetypes (2.3), the agent-based simulation (2.4), the multi-modal extension and its δ matrix (2.5), and the field-pilot and infrastructure pipelines (2.6).

2.1 The MNL Psychometric Cost Function

A pedestrian route *r* between origin and destination is a sequence of graph edges, each carrying measurable attributes. Following the additive-utility tradition of route-choice modelling [12, 13], we represent each walker's preference as a weight vector and define route cost as the weighted sum of cost-transformed attributes. Comprehensive reviews confirm that factors beyond time and distance shape path selection [14], and regret-based alternatives to utility maximisation have been proposed [15]; we retain the additive-utility form for its interpretability and closed-form weights.

$$C(r,p) = \sum_{k=1}^{8} \beta_k\,(p)\, f_k(r) \tag{1}$$

The eight cost-transformed attributes $f_k(r)$ are listed in Table 1; attributes for which a high raw value is desirable (scenic quality, reliability, lighting) are inverted so that higher cost always means worse.

Table 1
Eight cost-transformed route attributes feeding the cost function

k	Attribute	Transform	k	Attribute	Transform
1	Travel time	$T(r)$	5	Carbon emission	$K(r)$
2	Scenic quality	$1 - S(r)$	6	Crowding	$W(r)$
3	Elevation gain	$E(r)$	7	Weather exposure	$X(r)$
4	Reliability	$1 - R(r)$	8	Safety lighting	$1 - L(r)$

The weights $\beta_k(p)$ are not fixed; they are derived from the walker's personality profile $p = (O, C, E, A, N, SS)$ through a personality–attribute interaction matrix:

$$\beta_k(p) = \beta_{0k} + \sum_{j=1}^{6} \gamma_{kj}\ \Psi_j \tag{2}$$

where β_{0k} are eight baseline intercepts, Ψ_j are the six personality traits, and γ is an 8 × 6 matrix of interaction coefficients. Weights are floored at 10^{-4} to prevent sign reversal and normalised so that $\sum_k \beta_k = 1$. The γ matrix is the primary theoretical output of this work — a testable, falsifiable, reusable bridge between personality psychology and transportation modelling (Figure 1). In Phase 1, γ is populated from literature hypotheses (e.g. high Neuroticism increases weight on time, lighting and crowding); in Phase 2, γ is estimated empirically from a discrete choice experiment using Biogeme.

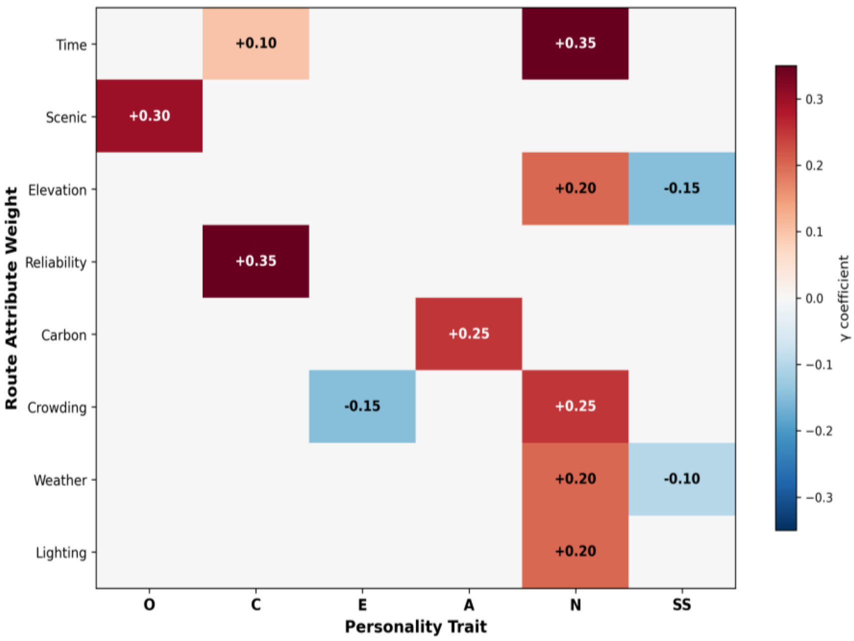

Fig. 1. The 8 × 6 personality–attribute interaction matrix γ — how each personality dimension modulates sensitivity to each route attribute (red = increased weight, blue = decreased)

2.2 Campus Digital Twin

The campus graph is built from OpenStreetMap pedestrian-network data for Boğaziçi University, Istanbul, covering four sub-campuses (South, North, Hisar, Uçaksavar) within the bounding box (29.0363, 41.0780) to (29.0573, 41.0918). Extraction uses OSMnx 2.x [16] with the “walk” network type, retaining all connected components. The resulting NetworkX graph contains 740 nodes and 1,892 edges spanning an elevation range of 4–135 m. Each edge receives the eight cost-function attributes; travel time is grade-adjusted with a Tobler-style hiking function, $t = (\ell / v)\,(1 + 3\,g^2)$, where ℓ is length, v walking speed, and g the slope. Elevation comes from SRTM 30 m data; stairway segments receive a fixed penalty (Figure 2).

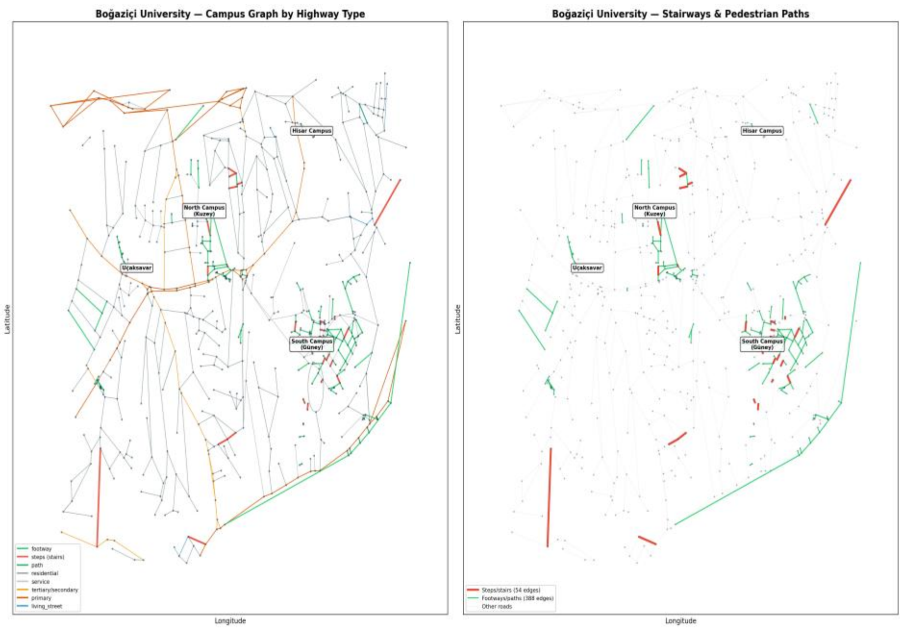

Fig. 2. Boğaziçi University campus graph (740 nodes, 1,892 edges); edges coloured by scenic score on the Bosphorus hillside (4–135 m elevation)

2.3 Psychometric Framework and Archetypes

Personality is measured with the Ten-Item Personality Inventory, Turkish adaptation (TIPI-TR) [17, 18], which reports the highest internal consistency of any TIPI translation (α = .81–.86) and completes in under three minutes; the 15-item BFI-2-XS is held in reserve as a higher-bandwidth backup. Five custom mobility items and two sensation-seeking items [19] complete a 15-item instrument. Raw responses are scored deterministically into a six-trait profile, then assigned to one of five canonical archetypes by nearest-centroid classification in trait space (Table 2), with assignment latency under 1 ms. Archetypes serve interpretability, efficient per-cluster LLM routing, and the group-and-distill cost strategy.

Table 2
Five canonical persona archetypes and trait centroids (O, C, E, A, N, SS)

Archetype (Turkish)	Key traits	O	C	E	A	N	SS
Efficient Commuter (*Verimli Yolcu*)	high C, low O	.35	.80	.45	.55	.50	.30
Explorer (*Kâşif*)	high O, high SS	.80	.40	.60	.50	.35	.80
Anxious Walker (*Tedbirli Yürüyüşçü*)	high N, low SS	.40	.55	.30	.55	.80	.20
Social Navigator (*Sosyal Gezgin*)	high E, high A	.55	.50	.80	.75	.35	.55
Eco-Conscious (*Çevreci*)	high A, mod. O	.60	.60	.50	.80	.40	.40

A deterministic pipeline — survey → scoring → classification → MNL weights → A* pathfinding — produces top-K candidate routes; an optional LLM re-ranking layer (GPT-4o-mini, temperature 0) adds qualitative context (weather, events, time-of-day) while leaving the core pipeline fully reproducible. This layer draws on recent persona-conditioned LLM agents for mobility simulation [20, 21] and on group-and-distill clustering, which performs inference once per archetype to bound API cost [22].

2.4 Simulation Design

Agent-based modelling accommodates the behavioural heterogeneity that aggregate models suppress [23]. The framework is exercised on a Mesa 3.x agent-based model [24] of 2,000 synthetic agents, each carrying a full OCEAN + sensation-seeking profile drawn from Turkish population norms (Atak, N = 926) via eigenvalue-clipped covariance sampling [16]. Mesa was chosen over MATSim [18] and SUMO [25,26] for its Python-native integration and adequate campus-scale performance. Each agent completes three campus trips per simulated day. Comparisons use Welch's t-test with Cohen's d effect sizes [27,28]; experiments run 30 replications per condition (10 for the paired multi-modal experiment), giving power > 0.80 for medium effects.

2.5 Multi-Modal Extension and the δ Matrix

The walk graph is replicated into a five-layer multi-modal network: walk (4.5 km/h, zero emissions), bicycle (12 km/h, 1.5× elevation penalty), scooter (18 km/h, 1.2× penalty, 15 g CO_2/km), shuttle and car, with inter-layer transfer edges. Mode choice is governed by a 5 × 6 personality–mode matrix δ analogous to γ. The multi-modal alignment score augments the base cost with a time-weighted mode-preference penalty (scale α = 0.3) and a per-transfer penalty (τ = 0.05), so the base cost $C(r, p)$ remains comparable across conditions.

2.6 Field Pilot and Infrastructure Pipeline

The field study follows a two-phase, KVKK-compliant (Turkish Personal Data Protection Law) design. Phase 1 deploys a Google Forms screening survey to build a classified participant pool; Phase 2 invites eligible participants into a two-week blinded A/B pilot through a Streamlit application, with persona-aware routing for the treatment arm and utilitarian shortest-path routing for control. A/B differentiation uses Yen's k-shortest paths bounded by a candidate pool, supplying persona-derived weights to one arm and fixed utilitarian weights to the other; alignment is always scored against the participant's own persona so the metric stays comparable. Route compliance is measured by an HMM map-matching pipeline with Viterbi decoding [29,30] against a spatial buffer. KVKK compliance is enforced through pseudonymisation, spatial cloaking (σ ≥ 50 m), k-anonymity and post-extraction GPS deletion. Finally, a p-median facility-location optimiser converts personality-segmented demand into infrastructure placement recommendations for scooter docks, bike racks and shuttle stops.

3. Results

Results are reported in five parts: the core persona-routing experiment (3.1), system-level applications (3.2), the multi-modal extension (3.3), real Phase 1 screening with δ-matrix validation and synthetic pipeline outcomes (3.4), and the infrastructure-design synthesis (3.5).

3.1 Experiment 1: Baseline vs Persona-Weighted Routing

The persona-weighted condition runs Eqs. (1)–(2) in full; the baseline uses fixed utilitarian weights approximating a commercial pedestrian engine. Across 30 runs of 2,000 agents, persona routing improves alignment significantly on all nine pre-registered tests at $p < .001$ (Table 3). The dual-level pattern is informative: run-level $d = 10.30$ indicates persona routing beats baseline in every run, while agent-level $d = 0.149$ reflects within-run heterogeneity. Per-cluster decomposition (Figure 3) confirms the hypothesised heterogeneity; the Reserved/Anxious archetype realises the largest gain (Δ = +0.0285, $d = 1.563$), while two clusters show small negative shifts, diagnosing attributes that Phase 1 γ underweights and that Phase 2 empirical re-estimation will correct.

A controlled elevation comparison isolates terrain effects. Introducing SRTM elevation lowers baseline alignment from 0.7214 to 0.7107 — the cost function now evaluates a richer attribute space, but the persona advantage persists at +0.0027 ($p < .001$), and walk times rise by ≈ 58 s as elevation-averse agents are routed around steep sections. The persona effect therefore survives realistic terrain (Table 4).

Table 3
Experiment 1 outcomes (means ± SD, 30 runs); all nine tests $p < .001$

Metric	Baseline	Persona	Cohen's *d*
Alignment (run-level)	0.7214 ± 0.0003	0.7245 ± 0.0003	10.30
Alignment (agent-level)	0.7214 ± 0.0145	0.7245 ± 0.0253	0.149
Walk time (run-level), s	2,073.9 ± 13.5	2,094.2 ± 13.4	1.488
Distance (run-level), m	2,592.4 ± 16.8	2,617.7 ± 16.7	1.487

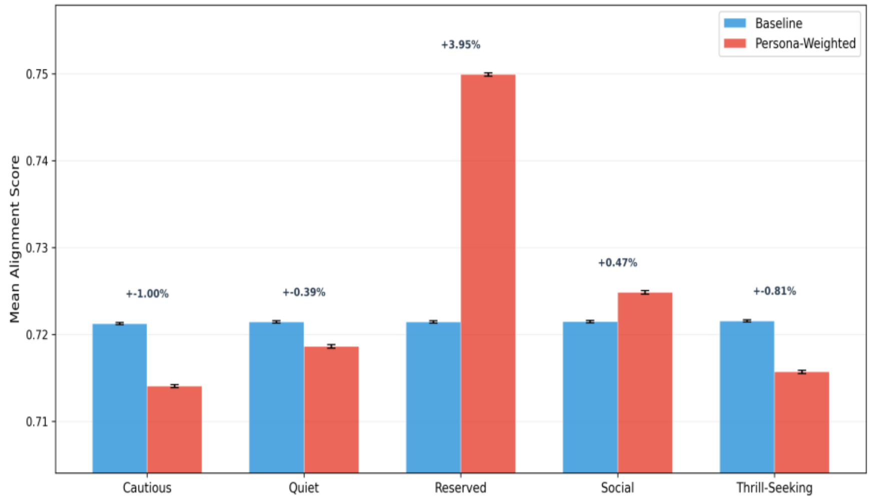

Fig. 3. Per-cluster alignment improvement. The Reserved/Anxious archetype gains most (Δ = +0.0285, *d* = 1.563); two clusters show small negative shifts, motivating Phase 2 γ re-estimation

Table 4
Elevation comparison: flat graph vs SRTM-integrated graph

Condition	Baseline	Persona	Improvement	*p*
Flat terrain	0.7214	0.7245	+0.0031	< .001
SRTM elevation	0.7107	0.7134	+0.0027	< .001

3.2 System-Level Applications: Fleet and Load Balancing

Two experiments extend persona routing from individual recommendation to system management (Table 5). In fleet rebalancing, a fleet of 30 scooters and 5 shuttles serving 500 requests reduces average wait time by 21.4 % (6.68 → 5.25 s, d = −0.747, p = .005) when vehicles pre-position by predicted persona-cluster demand rather than historical density. In behavioural load balancing, routing agreeable agents (Social Navigator, Eco-Conscious) onto alternative paths while granting anxious agents priority cuts peak congestion by 17 % (0.82 → 0.68 of capacity, d = −3.587, p < .001) during a simulated rush-hour convergence on a single building.

Table 5
System-level applications of persona routing

Experiment	Control	Persona-aware	Change	Cohen's *d*
Fleet rebalancing — wait time (s)	6.68 ± 1.73	5.25 ± 2.02	−21.4 %	−0.747
Load balancing — peak congestion	0.82 ± 0.05	0.68 ± 0.01	−17 %	−3.587

3.3 Experiment 4: Multi-Modal Transport

Across ten paired runs of 2,000 agents (60,000 trips), the multi-modal extension cuts travel time from 2,158 s walk-only to 1,236 s, a 43 % reduction, at a carbon cost of 64.7 g CO_2 per trip (Table 6). The mode split is walk 62.1 %, scooter 34.8 %, car 3.2 %, bicycle 0 %, shuttle 0 % (Figure 4). The zero-bicycle result is terrain-driven, not a model artefact: Boğaziçi's hillside imposes a 1.5× elevation penalty on cycling versus 1.2× for electrically assisted scooters, so bicycles never win on the candidate OD pairs. The finding is independently corroborated by Phase 1 survey data, where bicycle preference scored lowest of all modes (1.58 / 7; Section 3.4).

Table 6
Experiment 4 multi-modal outcomes (10 runs, 2,000 agents)

Metric	Walk-only	Multi-modal	Cohen's *d*
Travel time (s)	2,158 ± 15	1,236 ± 9	−75.0
CO_2 per trip (g)	0	64.7 ± 2.0	—
Transfers per trip	0	0.96 ± 0.01	—

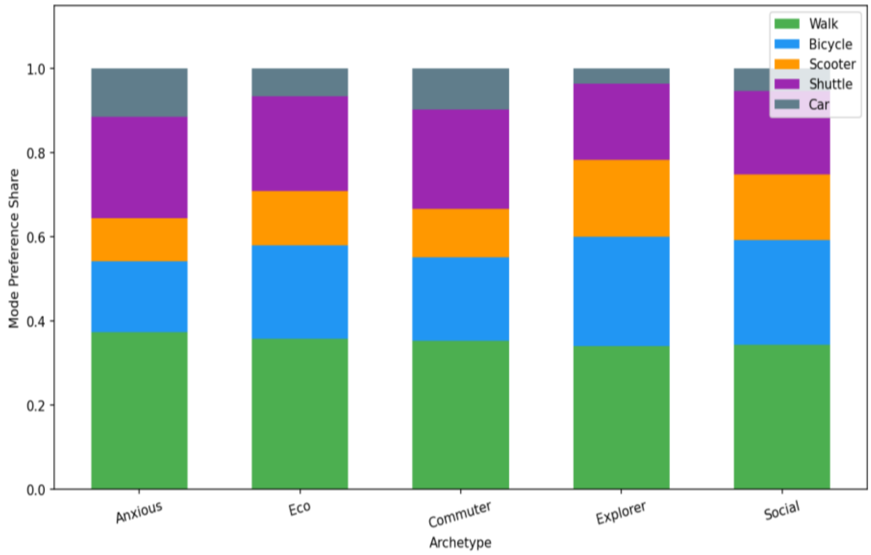

Fig. 4. Transport mode split: walk-only baseline vs persona-aware multi-modal. Scooters dominate non-walk choices (34.8 %); zero bicycle adoption is terrain-driven

3.4 Phase 1 Real Screening and Synthetic Pipeline Validation

Within 16 hours of deployment, 26 responses arrived, all from Boğaziçi undergraduates; eligibility screening (walking ≥ 3 times/week) retained 19 (73 %). The sample diverges sharply from Turkish norms (Table 7), with Extraversion (d = +1.86) and Sensation Seeking (d = +1.19) the largest shifts, consistent with self-selection in a student volunteer pool. The archetype distribution is heavily skewed: Social Navigator 46 %, Explorer 42 %, Efficient Commuter 8 %, Eco-Conscious 4 %, and zero Reserved/Anxious, the most important known limitation of the pilot as configured.

Table 7
Phase 1 trait divergence from synthetic norm population (n = 19 eligible)

Trait	Phase 1 mean	Synthetic mean	Cohen's *d*
Extraversion	0.78	0.49	+1.86
Sensation Seeking	0.73	0.48	+1.19
Agreeableness	0.70	0.56	+1.10
Openness	0.75	0.62	+0.83
Neuroticism	0.36	0.43	−0.42

The central empirical test of the framework is δ-matrix sign validation. With 19 eligible participants and Spearman correlations between trait scores and five mode preferences, 16 of 23 hypothesised δ sign directions are confirmed (70 %); under a null of random signs, the binomial probability of ≥ 16/23 is p = .047 (Figure 5). To the authors' knowledge, this is the first empirical evidence that personality–mode interaction coefficients reflect real choice behaviour. Replacing national-norm traits with the empirical Phase 1 distribution and re-running Experiment 1 lifts alignment by +0.019 (run-level d = +41.5, p < .001), showing that synthetic populations calibrated to country means systematically understate the alignment achievable at a given institution. Hence, campus-specific psychometric data are essential for simulation validity.

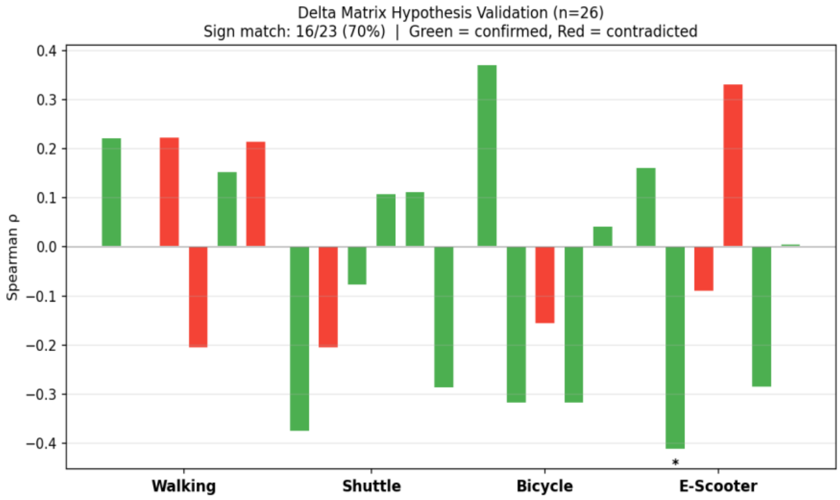

Fig. 5. δ-matrix sign-direction validation. Confirmed directions (16 of 23, green) versus contradicted (7, red); overall 70 %, binomial p = .047

A synthetic field dataset (n = 80 simulated participants; 70 post-survey respondents, 35/35 split) validates the analysis pipeline end-to-end before live deployment. The most informative pattern is a dissociation between objective and subjective outcomes: deviation and SUS show no group difference, while satisfaction (d = 1.169) and commercial viability (d = 1.445) show very large effects (both p < .001). These are pipeline-validation results, not field evidence. The generator embeds the hypothesis the live pilot exists to test, but if confirmed, the dissociation is the practical finding: persona-aware routing does not move pedestrians to dramatically different paths; it supplies routes whose attributes resonate with users' preferences, producing a sense of being understood by the system.

3.5 Infrastructure Design Synthesis

Applying the p-median optimiser to the Phase 1 archetype distribution yields actionable design outputs. The per-mode suitability profile (Figure 6) shows a 23-percentage-point gap between bicycle (53 %) and scooter (76 %) suitability, a quantitative explanation for the zero-bicycle / 35 %-scooter split. Persona-optimised placement achieves coverage of 0.815 versus 0.716 for uniform-demand placement, a 13.9 % gain at the same budget (Figure 7). This recommends an expansion from 6 to 8 docks, adding one at the currently unserved Hisar connector and shifting one toward the North Dorms cluster. At a conservative 8 % adoption rate, the long-run target is 23 scooter docks (230 scooters), deployed in three annual phases.

Translating routing and adoption results into civil-engineering KPIs yields the planning dashboard in Figure 8. Multi-modal deployment saves an estimated 2,397 person-hours per day (≈ 431,460 per year, ≈ 245 FTE-equivalents) across ~9,360 routable trips at 15.4 min saved per trip. The Gini coefficient of alignment across personality types is 0.007 — near-perfect equity, quantifying the claim that personalisation is itself an equity intervention, since utilitarian routing most underserves the personality profiles farthest from the mean.

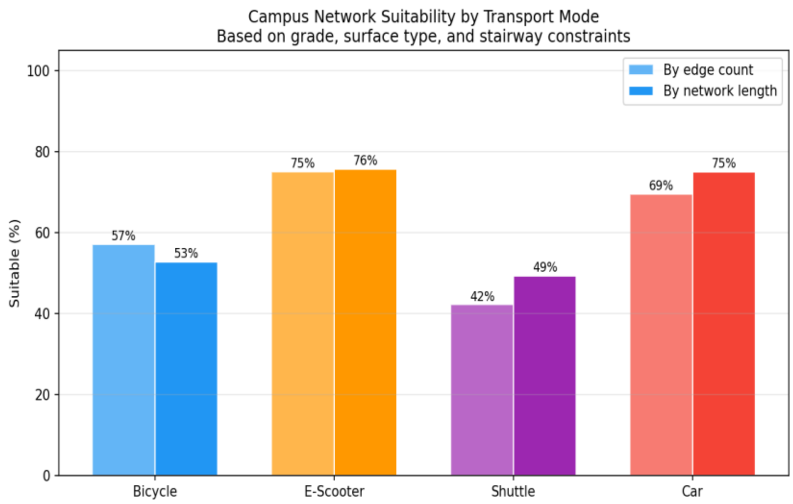

Fig. 6. Per-mode infrastructure suitability across the campus graph. Bicycle (53 %) trails scooter (76 %) by 23 points due to grade penalties

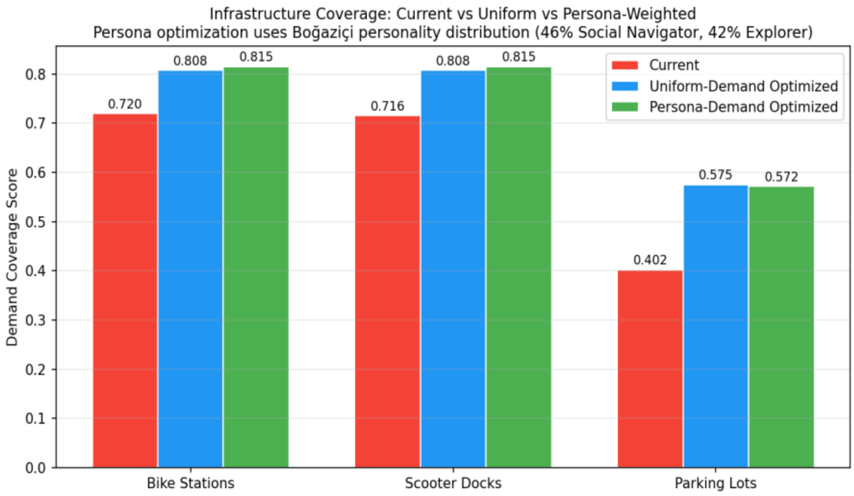

Fig. 7. Coverage comparison: persona-optimised (0.815) versus uniform-demand (0.716) placement, a 13.9 % gain at equal budget

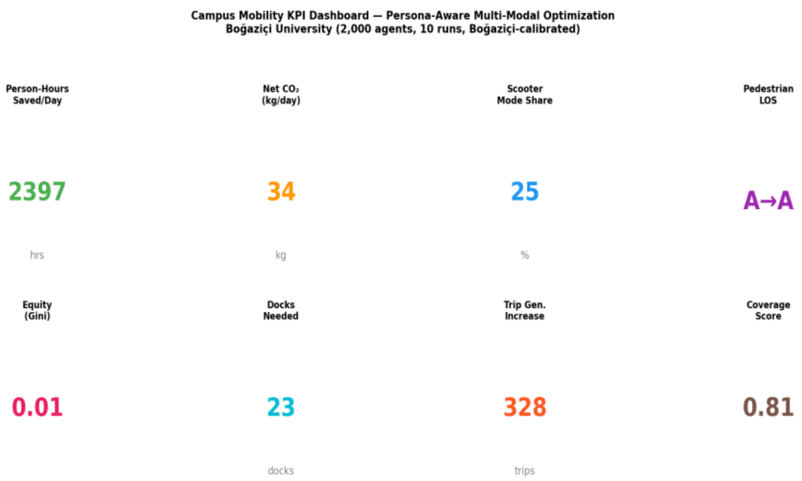

Fig. 8. Civil-engineering KPI dashboard: person-hours, equity (Gini), level of service, carbon, coverage uplift and infrastructure sizing on a single planning surface

4. Conclusions

Three claims structure the contribution. Claim 1 (simulation): supported. Persona-weighted routing achieved significant alignment improvement on all nine pre-registered tests at $p < .001$ (run-level $d = 10.3$), and the effect persists under SRTM-integrated terrain (+0.0027, $p < .001$). Claim 2 (field — Phase 1 real + pipeline): partially supported. Phase 1 produced the first empirical evidence that the hypothesised δ matrix captures real personality. Mode relationships (70 %, $p = .047$) and the pipeline validation confirm the analysis stack can detect large subjective-measure effects ($d > 1$). Claim 3 (multi-modal and infrastructure generalisation): supported. The multi-modal extension delivered a 43 % travel-time reduction with terrain-validated zero-bicycle adoption, and the p-median optimiser translated personality-segmented demand into a phased 23-scooter-dock plan saving 2,397 person-hours per day at Gini = 0.007.

The most theoretically informative pattern is the dissociation between objective behaviour and subjective experience. Persona-aware routing changes how walkers feel about their route more than where they walk. This aligns with discrete-choice theory, in which utility is a latent construct not fully captured by revealed choice. Conventional metrics (time, distance, deviation) systematically underestimate the value of personalisation because they focus on observable behaviour rather than subjective experience.

Several limitations limit the findings of this study. Phase 1 $n = 19$ validates δ's sign pattern but not stable trait correlations, and the archetype imbalance (zero Reserved/Anxious) requires targeted recruitment in Phase 2; live field data were not yet collected; SRTM 30 m is coarser than LiDAR; the two-week pilot captures adoption but not habituation; Phase 1 γ is literature-derived; and results are single-campus. Three priorities follow: empirical γ calibration via a discrete choice experiment analysed with Biogeme; multi-campus replication across contrasting topographies; and higher-resolution elevation with real-time environmental sensing. In summary, the 8×6 γ matrix is the primary theoretical contribution and the empirical primitive against which future work can be measured: personality and the infrastructure that routing depends on matter for routing.

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Conflicts of Interest

The authors declare no conflicts of interest.

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