Spatial Nudging: Converging Persuasive Technologies, Spatial Design, and Behavioral Theories

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Abstract

This paper presents the Spatial Nudging framework – a theory-based framework that maps out nudging strategies in the mobility domain and refines its existing definitions. We link these strategies by highlighting the role of perceived affordances across physical and digital interventions based on the Nudge Theory and the Theory of Affordances. Furthermore, we propose to use graph representation techniques as a supportive methodology to better align perceived and actual environments, thereby enhancing the intervention strategies' effectiveness. We illustrate the applicability of the Spatial Nudging framework and the supportive methodology in the context of an E-bike City vision. This paper lays the foundation for future research on theoretically integrating physical and digital interventions to promote sustainable mobility.

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1 Introduction

Promoting sustainable mobility, particularly cycling, is crucial for combating climate change [5] and enhancing overall well-being [10]. Various strategies exist, oscillating between *hard* measures such as policies or infrastructure planning [3], and *soft* measures such as Mobility as a Service (MaaS) offerings [48], or digital tools supporting societally desirable or personalized travel goals [46]. Jensen et al. [28] refer to the combination of these strategies as *Mobilities design* emphasizing its behavioral goal-oriented nature.

Creating safe and comfortable bike lanes through infrastructure changes is widely recognized as a highly effective intervention strategy [32], with behavioral change evidence from multiple empirical studies [60, 20]. Despite this, persuasive technologies such as mobile applications that use nudging strategies, i.e., subtle interventions that aimed at predictably influencing travel habits, gained the attention of policymakers as well as location-based service providers [50, 46]. In a recent review, such applications were found to reduce car use by approximately 7%, illustrating that digital communication strategies and targeted informational campaigns influence travel behavior [51]. A nudge is a subtle change in how choices are presented or organized within the choice environment [53]. The choice environment is the

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setting where decisions are made, including physical spaces, digital interfaces, or augmented reality (AR) [31]. According to Thaler and Sunstein [56], these choice environments inherently influence decision-making and are unavoidable.

However, goal-oriented design elements or persuasive applications in physical and digital environments face challenges in shaping our travel choices. In the context of physical interventions, research has identified a cognitive mismatch between the objective (observable) properties of the physical environment shaped by planners and the subjective perceptions of users [58]. Similarly, digital nudges promoting cycling must resonate with these user perceptions to be effective [51]. In turn, accurately anticipating how users perceive physical environments or react to digital nudges is challenging, posing a major obstacle to effective interventions. Furthermore, the theoretical links between these choice environments remain fragmented. For example, views differ on whether infrastructure design itself constitutes a nudge [20] or merely provides context information for the nudge design [32]. Moreover, while interventions informed by the psychological theories are hypothesized to show greater efficacy [33], the multitude of existing theories complicates choosing when and how to apply them in daily planning tasks [13].

To ground nudging more cohesively in the mobility domain as a multifaceted behavioral change strategy, there is a need to develop a clear and unified definition of nudging strategies across choice environments. Additionally, supporting methodologies are essential to better anticipate how physical environments influence subjective perceptions and responses to nudges, thereby increasing the effectiveness of these strategies. Our approach begins with a thorough overview of various nudging strategies for sustainable mobility and leveraging relevant theories, such as the Nudge Theory [56] and the Theory of Affordances [22] to identify the role of the physical environment in these strategies. Secondly, we evaluate methodologies that enable the analysis of the impact of people's perceptions on travel behavior. Graph representation stands out as a feasible solution for our needs, with its proven effectiveness across urban informatics [57], urban planning [52], and cognitive studies [62].

This paper introduces the Spatial Nudging framework which maps out nudging strategies in the mobility domain by highlighting the role of perceived affordances across physical and digital interventions based on related behavioral theories. We propose a novel concept called Spatial Nudging – an integrated nudging strategy that utilizes multiple choice environments, nudging techniques and spatial information to design an intervention for behavior change, thereby extending the scope of existing nudging strategies. Furthermore, we present initial steps for a supportive methodology to align perceived and objective environments of cycling routes, specifically in a route recommendation task. We illustrate the applicability of the Spatial Nudging framework and the supportive methodology in the context of the E-bike City project [3].

The paper is structured as follows: section 2 covers nudging and related behavioral theories, cognitive mismatches, and current graph-based methods for analyzing travel behavior. Section 3 elaborates on the Spatial Nudging framework, the initial conceptualization for the supportive methodology, and an illustrative use case. Section 4 concludes with the key contributions and directions for future research.

2 Background

In this section, we discuss the existing theoretical underpinnings used to conceptualize nudges across physical and digital interventions for sustainable mobility behavior, particularly cycling. Then, we delve into the difference between how physical environments are perceived versus their objective characteristics and how these environments affect nudging efforts. Finally, we explore graph-based methods' potential to anticipate this mismatch better.

2.1 Nudging and Related Behavioral Theories

Human decision-making related to mobility is not always rational and often relies on mental shortcuts and habits that can be influenced through changes in choice environments [63]. Nudging refers to the practice of subtly steering individuals towards better options by strategically organizing and delivering information in these choice environments [53, 16]. The nudge concept is rooted in Nudge Theory, which asserts that (1) the choice environment notably influences how people make choices, (2) choice architecture is unavoidable, and (3) it is possible to nudge while preserving freedom of choice [56].

Different nudging conceptualizations have emerged, such as Hummel's morphological box [27], suggesting multiple perspectives on how nudges are defined across domains. In Table 1, we present an overview of such attempts to structure and characterize nudges based on where, how, and what nudges target. This overview reveals overlapping, complimentary, yet contrasting descriptions of nudges, illustrating fragmented and often ambiguous distinctions between different strategies, particularly regarding the role of the physical environment. For instance, many consider physical interventions, such as strategic placement of items and signifiers or bike infrastructure design, as forms of nudging [31, 20]. Meanwhile, in the development of persuasive technologies, spatial characteristics are primarily interpreted as the contextual background information for designing more effective digital nudges [32].

Travel behavior change strategies, including nudging, draw upon various behavioral theories [30, 45, 67]. For example, the *Mobility design* paradigm [28] mentioned earlier is based on the Theory of Affordances, initially introduced by Gibson [22] and later elaborated by Norman [42] who emphasized the relation between perception and affordances. The Theory of Affordances examines the psychological interactions between humans and designed objects. *Affordances* represent perceived potential actions available to a user and are integral to an object's design. Sunstein [54] extensively references design examples described by Norman, while Lehner et al. [31] frame nudging tools as valuable design principles, highlighting a close link between nudges and design intent. In the mobility domain, the theory highlights how individuals engage with the physical elements, including infrastructures, as well as digital tools like smartphones with GPS services that are brought along on everyday journeys [28]. These examples illustrate how nudging can be framed as a strategic design effort to shape perceived affordances within physical and digital choice environments, potentially offering a foundation for a design-based perspective on existing nudging definitions.

2.2 The Mismatch of the Objective and Perceived Environments

The effectiveness of strategies – goal-oriented design interventions or nudging – that encourage cycling partly depends on people's perceptions, as perceptions are known to influence travel behavior [34]. The intervention strategies discussed below showcase two perspectives on perception: one focuses on its influence in universal interventions that target everyone and is typically associated with the physical choice environment, while the other emphasizes its role in personalized interventions and is more common across digital choice environments.

Research on the effect of physical interventions for cycling reveals a cognitive mismatch between planners' objective evaluations and users' subjective perceptions [58]. This mismatch has been explored in aspects such as cycling speed [41], travel time [44], and infrastructure design [37]. The mismatch originates from complex cognitive processes where an individual's sensory inputs (experienced trip utility) are translated into a cognitive representation of the environment (recalled trip utility) [17]. Many factors, such as physical activity [38], demographics [34], local culture [1], as well as attitudes [18], habits [49], and cognitive

Table 1 Showcases existing nudging categorizations relevant to the mobility domain based on where, how, and what nudges target to change travel behavior.

Category / Key Elements	Description
	What nudges target
1. Cognitive System - Cognitive System 1 - Cognitive System 2	Nudges target *System 1*, exploiting cognitive biases, or *System 2* that aims to encourage rational thinking. This differentiation stems from the dual process theory [29].
2. Decision-making System - Decision structure - Decision information - Decision assistance	Nudges can target the *decision structure* (how choices are organized), *decision information* (details about the choice options), or *decision assistance* (supporting behavioral intentions). Interventions focusing on the decision structure typically have a stronger effect [40].
3. Stage of Behavioral Change - Pre-contemplation - Contemplation - Preparation - Action and Maintenance	Nudges target behavior at different stages of the behavioral change process [12]. Nudges in the *pre-contemplation* stage aim to boost awareness. Nudges that target *contemplation* assist self-assessment. During the *preparation* stage, they reinforce self-commitment and further educate about alternatives. Nudges targeting *action and maintenance* reward positive behaviors and build social support.
4. Goals - Sustainability	Nudges target different *goals*. For instance, green nudges encourage sustainability in energy conservation, mobility behavior, or food consumption [69].
5. Choice Environment - Properties - Placement	Nudges can change the *properties* of the choice environment, *placements* within, or both [26].
	Where nudges target
6. Choice Environment	Nudges target travel behavior in different choice environments, including *digital* or *physical* [31, 27].
- Physical environment	Physical nudges guide decision-making in physical choice environments. While minor alterations such as signage or road markings are prime examples, larger-scale modifications have also been called nudges [8, 20].
- Digital environment	Digital nudges guide decision-making in digital environments and have been associated with digital user interfaces [69]. Examples include persuasive elements in mobile or web-based applications [12].
	How nudges target
7. Level of Obtrusiveness - Invite - Seduce - Challenge	Nudges vary in their level of obtrusiveness. Nudges that *invite* are highly open and voluntary, while *seductive* nudges lure with appealing offers. Nudges that *challenge* engage people's competitive nature. However, creating barriers is too intrusive to be considered a nudge [59].

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Category / Key elements	Description
8. Strategy - Educative - Social - Environmental - Incentive	Nudging can be defined by the overall strategy [4]. *Educative* nudges inform individuals about their decisions. *Social* nudges leverage social comparison and *incentive* nudges involve offering rewards. *Environmental* nudges modify the needed effort for the behavior by changing the choice order or visibility.
- Gamification	Nudges use game elements in non-gaming contexts and leverage common game mechanics such as *competition*, *cooperation*, *quests*, *points*, or *badges*. [11, 33].
9. Personalization	Nudges vary from *universal* approaches targeting wide audiences to *personalized* interventions designed for individual preferences. While universal interventions may neglect unique individual situations, personalization can limit shared experiences important for policy transparency and identity development [39].
- Universal	Generic digital nudges or physical interventions that target behavior universally across broad user groups are prime examples of universal nudging [8].
- Personalized - Delivery Personalization - Choice Personalization	Nudges utilize diverse data to personalize the choice by customizing outcomes (*choice personalization*), or the method of nudge (*delivery personalization*) [39].
- Context Awareness	Context-aware nudges use location-based services to determine the individual context, e.g., demographics, built environment, weather, or public transport schedules, to inform nudging strategies [32, 11]. This approach addresses criticisms of digital nudging, which often reuses generic nudges without considering local contexts [33].
- Location-based - Suggestive - Disclosure	Nudging varies based on the beneficiaries, influenced by the design of location-based services. *Suggestive* nudges benefit only individuals to achieve their goals. In contrast, *Disclosure* nudges, which push for sharing location data to improve navigation, can limit free decision-making by over-relying on GPS and exposing personal data to service providers [25].
10. Tool or Technique	Various common nudging tools exist: *feedback, self-monitoring, prompting, reminders, tailoring, framing, simplification, priming, changes in physical environment, visibility or accessibility, social comparison, social norms, saliency, signifiers, defaults, goal-setting, anchoring, rewards* [31, 21, 33, 32, 50, 53]. Notably, the conceptual links and hierarchies across these techniques are ambiguous.

biases [21] can affect how physical environments are perceived. Therefore, accounting for these factors contributing to the aforementioned mismatch is vital for successful physical interventions.

Perception also plays a role in designing and determining the success of digital interventions such as persuasive mobile applications aimed to influence travel choices [64]. These applications engage with perception in two ways: 1) their effectiveness heavily relies on the perceived physical environment, and 2) they often target human heuristics to influence perceived affordances and nudge individuals towards more desirable travel choices. Specifically, for digital nudges to effectively promote active mobility, they need to align with positive users' perceptions of their physical environment such as weather, cycling infrastructure, or presence of greenery [32, 51]. This highlights the importance of the physical environment in digital strategies and the need to understand user perceptions, particularly among diverse user groups, to design effective digital nudges [50].

2.3 The Role of Graphs in Travel Behavior Analysis

Various methodologies help to understand, analyze, and predict travel behavior and the underlying reasons [46]. A significant trend in the existing literature is the use of mathematical graph representations in cognitive studies related to spatial knowledge [62], urban planning [52], and individual mobility analytics [65]. Despite the extensive research within individual domains, studies that derive combined insights for the mentioned applications of graph data structures are absent, presenting an opportunity to explore potential synergies. However, these applications of graphs vary across scales, granularity, and levels of abstraction, requiring comprehensive alignment.

Spatial knowledge and potential movement actions can be represented using graph-like elements [66]. For instance, supported by multiple empirical studies, the Cognitive Graph hypothesis proposes using a labeled graph with local metric information embedded in graph nodes and edges to represent spatial knowledge, akin to cognitive maps [62, 6]. Recent studies show that graph-based models incorporating spatial biases and heuristics can generate realistic movement trajectories [19, 35]. In a related stream of work, the Space Syntax community typically uses standard graph-based measures to reveal psychological responses to urban form, also seen in studies for planning bike networks and analyzing cyclist behavior [52]. Urban planners have a long tradition of using this approach for its predictive ability and easy translation to policies for promoting active mobility [68].

Urban analytics and trajectory data mining are key for studying travel behavior [61] and testing assumptions about human mobility heuristics at scale [55, 9]. Topological (graph-like) representations of movement data are argued to offer additional structural information about human mobility [65]. For example, researchers use graph representation and standard graph measures to recommend personalized routes [57]. Martin et al. [36] propose compact and privacy-preserving location graphs to profile trajectory data across multiple datasets. In a related study, Wiedemann et al. [65] leverage such location graphs with social network science methods to reveal structural patterns in individual human mobility. Bongiorno et al. [9] use a vector-based method, revealing heuristics such as detour percentage in pedestrian route choices at scale.

3 Spatial Nudging Framework

This section introduces the Spatial Nudging framework to unify the fragmented understanding of nudging strategies and their characteristics in the mobility domain across different choice environments. We further outline a graph-based method to support (nudge) route choices, an essential travel choice task, by potentially aligning perceived and actual environments better – an essential factor for the success of these strategies. Finally, we present an illustrative use case for its applicability in the context of Zurich.

3.1 Rationale and Framework Development

Based on the literature overview in section 2, we provide a rationale for theoretically integrating the fragmented nudging strategies and affordances of different choice environments. Our approach considers the varying perspectives on the role of physical environments across different interventions.

First, we scrutinize the common contrasting notion that nudging is used to bypass the challenges associated with physical interventions, such as regulatory complexities and high costs. Our literature review illustrates that nudging and physical interventions are not mutually exclusive and multiple underlying techniques share similarities. For example, visible bike lane markings, arguably a physical intervention, could be viewed as a nudging technique that increases bike lane saliency, i.e., it modifies the properties of the choice environment (see Table 1, Category 4.). Furthermore, the assumption that nudging is a cost-effective and straightforward alternative for behavioral change overlooks the extensive processes required to develop effective nudges, including designing, testing, aligning nudges with existing preferences, and finally implementing it [16].

Second, we examine the reasons behind differing views on whether a physical intervention qualifies as a nudge, and more broadly, the role of choice environments across interventions. The literature review reveals that these differing views often map to specific disciplinary domains. Arguably, the domain's ability to target perceived affordances is bound to different choice environments, expertise, timelines, and methods. For example, experts who create digital tools to assist travel decisions typically view the physical environment as unchangeable, while planners consider it malleable due to their expertise. Context-aware persuasive technologies serve as a unique nudging case in this divide. They intertwine physical and

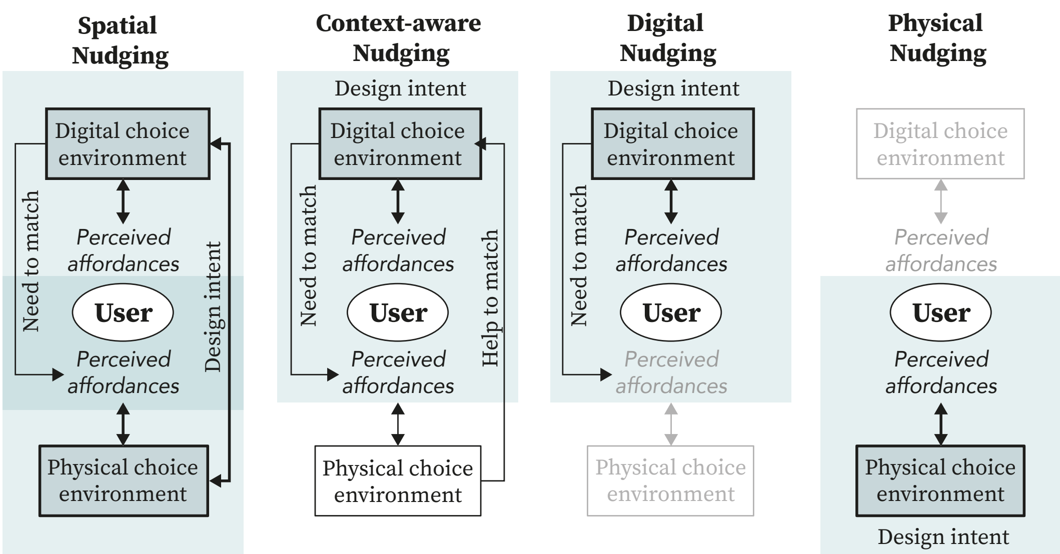

Figure 1 Illustrates the interaction between choice environments, perceived affordances, and users across discussed nudging interventions, demonstrating how each type of intervention reflects Spatial Nudging to different extents.

digital choice environments by leveraging information from the physical environment to design more tailored digital nudges [32]. Although current examples do utilize contextual information, they often do not consider the physical environment's ability to influence perceived affordances – a crucial aspect of its design according to the Theory of Affordances. Despite this, context-aware nudging offers a useful starting point for integrating behavioral change efforts across both choice environments.

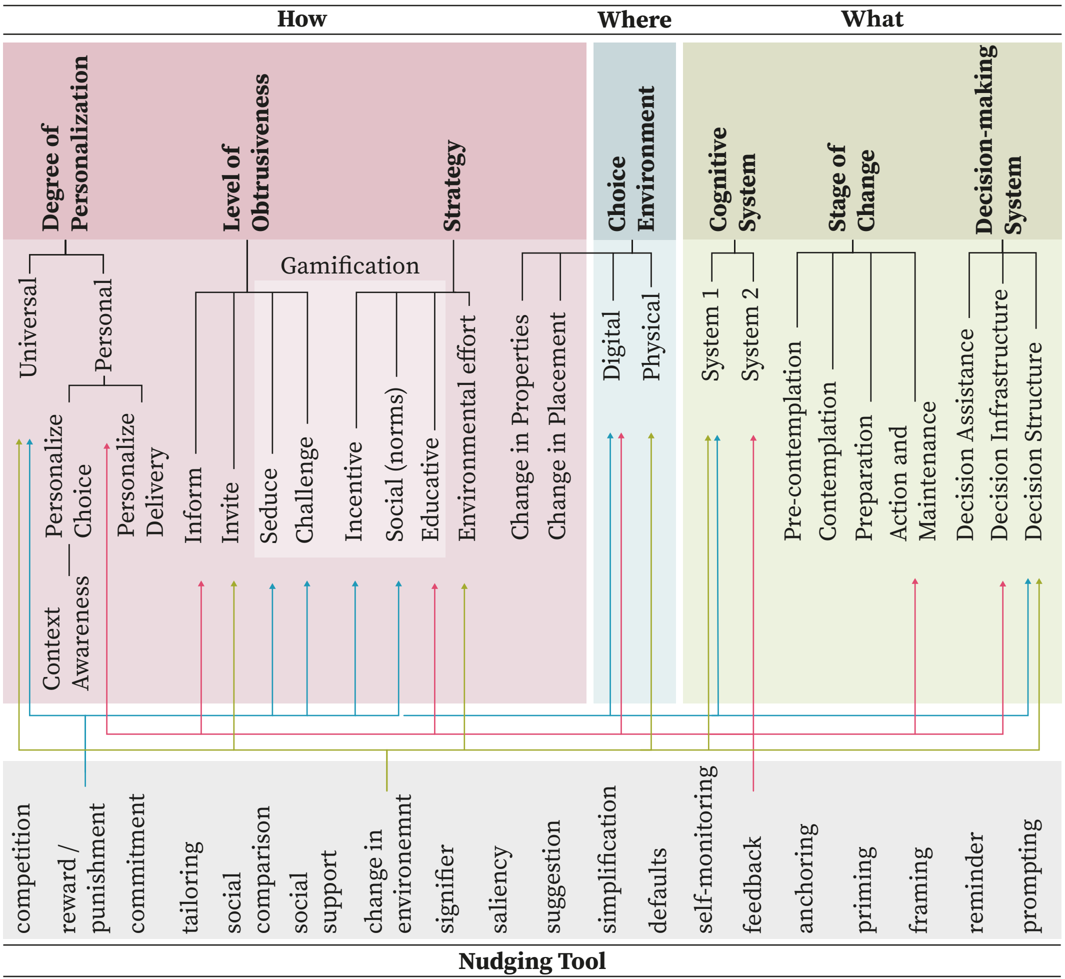

Figure 2 Illustrates how common nudging categories can describe three hypothetical examples of nudging interventions discussed in this paper. Although these examples are hypothetical nudging interventions, the mapping could be similarly applied to existing ones. Pink lines describe context-aware nudging, e.g., a mobile app displaying trip CO_2 emissions. Green lines refer to a physical nudging, e.g., a strategic placement of a new bike lane. Blue lines refer to digital nudging, e.g., a mobile app with gamification and reward strategy for traveling sustainably.

Therefore, we propose the Spatial Nudging framework, which explicitly outlines the links between the physical and digital choice environments and different nudging interventions to promote active mobility. Drawing on multiple examples from Table 1 that support the idea of nudges functioning as design principles, we propose four distinct nudge strategies by linking choice environments, perceived affordances, and design intent. Figure 1 and the descriptions below outline these strategies: physical, digital, context-aware, and spatial nudging. The figure also highlights findings from existing literature, suggesting that nudges in the digital choice environment must align with the perceived physical environment to be effective. However, our review of related active mobility research found no evidence that digital tools need to alter perceptions of the physical environment for physical interventions to be effective. While we focus on nudging within physical or digital choice environments, as they are predominantly used in current behavioral change strategies to promote cycling, AR could serve as a potential choice environment that would allow for testing whether an overlay of virtual information changes perceived physical cycling affordances. Similarly, this study does not cover the influence of social networks, local culture, or regulatory systems as potential choice environments.

- **Physical Nudging**: refers to interventions in the physical choice environment. Examples include the strategic placement of signs and increasing visibility of bike lanes or parking markings with vibrant colors.
- **Digital Nudging**: is embedded in a digital choice environment and communicated via digital interfaces. Examples include motivational prompts or gamification techniques in mobile applications that promote sustainable mobility.
- **Context-Aware Nudging**: is embedded in the digital choice environment but utilizes contextual data to match nudges with individual context and expectations better. Examples include mobile trip planners leveraging weather conditions, traffic updates, or air quality indices.
- **Spatial Nudging**: refers to strategies that simultaneously utilize several choice environments, with spatial information linking these environments. Examples include dynamically allocating road space and enhancing communication about the current state or prioritizing physical interventions according to the most popular routes suggested by digital trip planners.

Additionally, we provide a comprehensive and refined nudge categorization, summarizing the key nudge categories based on Table 1 and considering where, how, and what nudges target. It can be argued that every nudge intervention presented in this study should have a mapping in each key category. Notably, while some of the identified categories can function independently, others show more interdependence. For instance, the physical choice environment typically targets everyone universally, illustrating interdependence between choice environments and degree of personalization. Similarly, individual nudging techniques are more likely to be leveraged in specific strategies. For instance, gamification often uses rewards, social comparison, or goal-setting techniques. Figure 2 provides a semi-hierarchical overview of these categories and three hypothetical examples of the discussed nudging intervention types mapped out across these categories.

3.2 Cognitive Graphs for Nudging Strategies as Supportive Methodology

As discussed in section 2, graph representation could be leveraged to anticipate better the subjective perceptions of physical environments and the reactions to nudging strategies, a necessity for successful interventions. Route choice is arguably one of the key tasks of determining travel behavior, influenced by the perceived affordances of route characteristics. Therefore, given its frequent targeting by physical and digital interventions, we focus our proposed supportive methodology on the route choice task. For an initial conceptualization towards a robust solution, we adopt a workflow by Dubey et al. [19] that proposes the Dynamic Hierarchical Cognitive Graph (DHCG), originally designed to generate realistic pedestrian trajectories while accounting for spatial memory biases and hierarchical nature of spatial knowledge. The DHCG dynamically encodes decision points, such as landmarks or road intersections, as a hierarchical abstract graph, used to search for the shortest network path to the destination (given an edge weight function) at each step of the route planning task. We argue that this approach is also suited for modeling spatial knowledge along constrained cycling routes. By modeling cycling routes dynamically, we can have a step-wise representation of perceived affordances along that route and can create a mapping between a particular decision point in the route and the associated perceived affordances. The methodology could suggest salient routes in mobile route planners, and capturing perceived affordances along the routes could be leveraged in many urban modeling and planning applications.

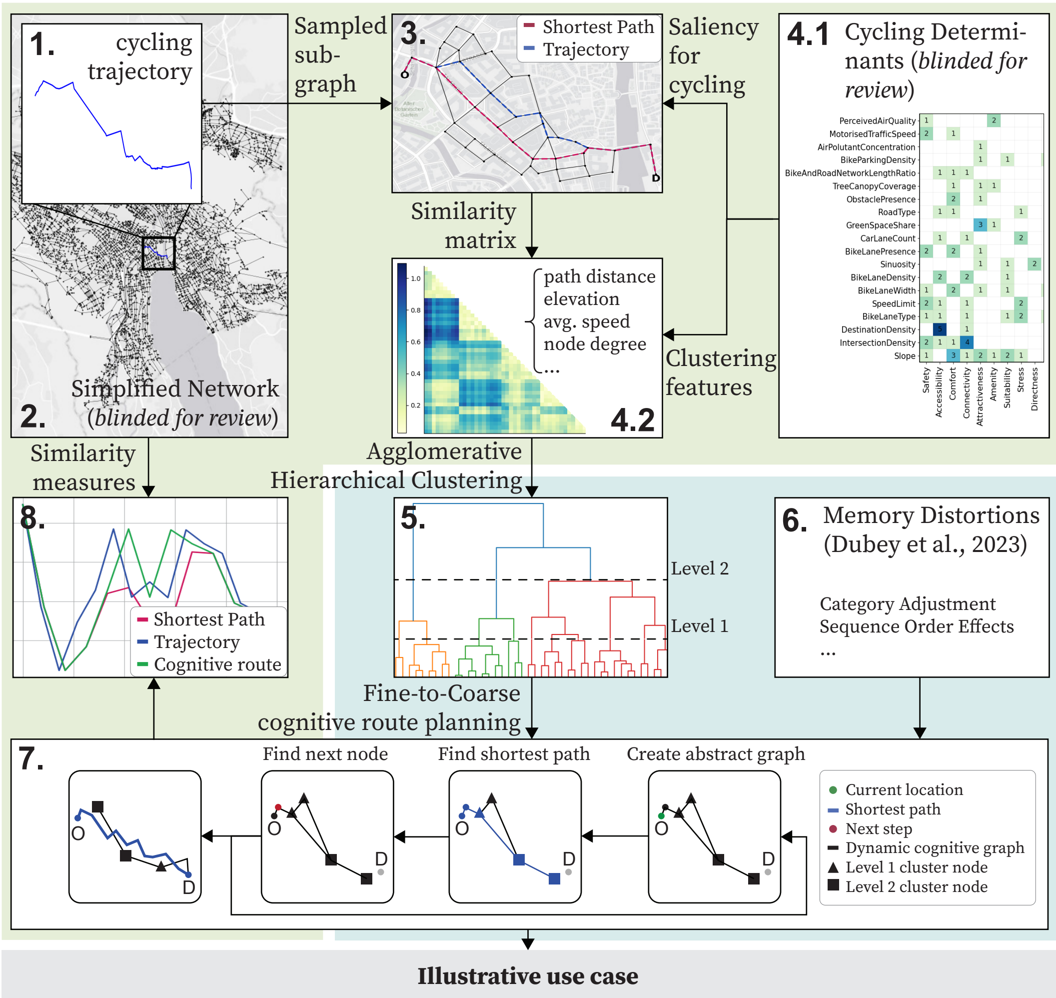

Figure 3 Illustrates the adapted workflow steps for creating cognitive routes. Components in green are customized and tailored for our cycling routing application, and components in blue are direct adoptions from [19].

The adapted workflow for generating realistic cycling routes consists of eight steps, summarized below and in Figure 3. Notably, steps 1-4 and 8 are novel cycling-specific steps that we introduced, while steps 5-7 are implemented according to the original workflow proposed by Dubey et al. [19]. Next, we describe individual steps.

First, we match existing cycling trajectories using Open Street Routing Machine (OSRM) API [43] (1) with a simplified graph-based road network (2). We create a feasible subgraph from the network for every trajectory by sampling unique network nodes and edges common to all possible paths that are up to 15% longer than the shortest path between the origin-destination (OD) pair of our cycling trajectory data as movement trajectories rarely follow the shortest possible path (3). The exact value for detour ratio is based on the research by Bongiorno et al. [9], and similar, albeit more heterogeneous, findings for cycling detours [7, 14]. Next, each node in the subgraph is enriched with metric attributes commonly used as cycling determinants to evaluate bike networks, such as traffic volume, slope, presence of bike lanes, and so forth (4.1). While Grisiute et al. [24] describe bike network evaluation metrics in detail, in this workflow, we only use a selection of metrics based on their frequency in the related literature. We define a pairwise similarity matrix for all nodes, where lower values map to higher similarity (4.2), and construct a cycling saliency value for every node.

Next, following the steps in the original workflow by Dubey et al., we cluster network nodes based on the similarity matrix using an Agglomerative Hierarchical Clustering (AHC) with the *complete* linkage method (defines the similarity of any two clusters based on the similarity of their most dissimilar pair) (5). The resulting dendrogram is truncated at specific heights to discern a three-tier hierarchy of clusters mirroring human spatial memory [35] as abstract cluster nodes later used in the route planning task. Notably, the first level (L1) is defined by the physical nodes in the subgraph. The subsequent levels, L2 and L3, are derived from the square roots of the number of clusters at the previous level. According to the authors of the original workflow, this approach aims to minimize the average size of the potential abstract graph, reducing the cost of path planning. Further, we integrate two models for spatial memory distortions (Category Adjustment (CA) and Sequence Order Effects (SE)) to adjust the locations of every cluster node (6). We then employ the Fine-To-Coarse (FTC) wayfinding heuristic for path planning [66], which uses a detailed mental representation of the immediate environment (L1 nodes) and gradually transitions to a coarser mental map of the environment (L2 and L3 cluster nodes). This mental representation is constructed dynamically as an abstract graph between the node at the current location and the destination node at every step (7). The movement cost between nodes, used to determine the next step in the abstract graph, is defined as a function equally balancing shortest-path distance and the physical or abstract node saliency value (by default, each weighting equally). Lastly, using different distance measures, we extend the original workflow with a pairwise comparison between the generated cycling route, the original trajectory, and the shortest path (8).

Ultimately, this workflow overview aims not to discuss individual steps in great detail but to provide an initial outline for one method to model perceived affordances dynamically. It aims to support the Spatial Nudging framework regarding route choice, a common target of physical and digital nudging interventions, which we illustrate next. To compare our workflow adoptions for cycling with the original workflow, please refer to the paper by [19] and Figure 3, where the parts in the green background represent our contributions, while those in grey depict the steps directly adopted from the original workflow.

3.3 Illustrative Demonstrator – E-bike City

The E-bike City project [3] is a significant initiative to promote cycling and reshape Zurich's transportation landscape by reallocating appr. 30% of road space to bike lanes, consequently reducing the number of car lanes. While the current strategy is infrastructure planning, one must also consider the influence of digital tools accompanying travelers and related nudging strategies on travel behavior. The stage of ongoing design is an ideal opportunity to

Table 3 Shows selected common bike network evaluation metrics and associated qualitative criteria for evaluating and designing bike networks. The metrics describing linear facilities (network edges), such as lane count, have been aggregated on nodes based on incoming edges. Public space significance and destination density are based on data from the City of Zurich and the Swiss Mobility and Transport Microcensus (MTMC).

Feature	Weight	Metric Type	Criteria	Source
Node degree	0.1	Graph	Coherence	OSM
Public space significance	0.1	Contextual	Attractiveness	City of Zurich
Destination density	0.2	Contextual	Attractiveness	MTMC
Slope	0.2	Morphological	Comfort	OSM
Incoming bike lanes	0.2	Infrastructural	Comfort	OSM/Planned
No. of car lanes	0.1	Infrastructural	Safety	OSM/Planned
Avg. speed limit	0.1	Modal	Safety	OSM

conceptualize and link prospects for different interventions from the outset. Utilizing the outlined workflow to generate realistic cycling paths enables us to 1) suggest salient routes for mobile route planners, and 2) compare how the newly proposed network dynamically affects the saliency values, perceived affordances, and potential route choice for existing trajectories.

To test the workflow, we utilized existing cycling trajectory data collected in Zurich in 2017 (users=36, trips=145). Notably, from the original dataset we excluded trips under 500 meters (i.e., OD pair is within 500 meters), circular trips, and trajectories in areas with low network density due to the limited choice alternatives such a network prescribes. Table 4 provides an overview of the resulting dataset composition. Despite the dataset's significant underrepresentation of females, other characteristics remain relatively similar across sub-groups. We sampled a representative trajectory for every remaining user in the filtered trajectory dataset (n=27) since routine trips with the same trajectories are common in this dataset.

For steps 1-4 of our workflow, we used a simplified existing road network graph for Zurich, generated from the Open Street Map (OSM) network with the SNMan Python toolkit which essentially simplifies the OSM network to represent intersections, and road segments as single nodes and edges [2]. We enriched the graph nodes (intersections) with metrics (see Table 3), mirroring criteria, and weighting ratios widely used to design and evaluate bike networks [15, 24]. Using the same metrics, we determined a cycling saliency value. Next, we performed steps 5-8 of the proposed workflow to generate corresponding cognitive routes and perform pairwise comparisons for every trajectory. We use the cognitive route term to refer to the generated trajectories based on DHCG and cycling saliency values.

Table 4 A descriptive overview of the initial cyclist trajectory dataset in Zurich. We consider peak hours to be between 7-9 am and 4-6 pm.

Attribute	Total	Female	Male
Trip (n=)	145	9	135
Cyclist (n=)	36	5	31
Duration (avg.), minute	7.19 (±5.10)	5.13 (±2.62)	7.32 (±5.20)
Length (avg.), meter	2766.52 (±982.18)	2815.61 (±830.31)	2763.27 (±993.96)
Age (avg.), years	45.80 (±7.33)	44.88 (±10.61)	45.86 (±7.11)
Peak Hour trips (n=)	40	4	36

The results summarized in Table 5 show that cognitive routes resemble the original trajectories more closely than the shortest routes without further calibration for individual variations. Notably, although optimizing the criteria weights for individual users to generate the most accurate results across trajectories is necessary, it falls outside the scope of this study. As a proof of concept, these results illustrate that our approach dynamically captures the perceived affordances for cycling and could be transferred into mobile trip planners to suggest more salient routes, acting as a digital nudge. Additionally, we compared the generated cognitive routes of the same trajectory for the existing and planned network scenarios. Figure 4 shows the differences in the cognitive routes and the corresponding cycling saliency values along each route. As a proof of concept, these results demonstrate that when applied at scale, this workflow could inform about the changes in perceived affordances created by physical interventions, i.e., a physical nudge. Both examples illustrate that this methodology can better capture the perceived affordances of the physical environment, potentially supporting physical and digital nudging strategies.

4 Discussion and Conclusions

In this study, we present the Spatial Nudging framework to theoretically unify the fragmented understanding of nudging strategies in the mobility domain. Consequently, the framework links nudging within interrelated domains such as transportation, urban planning, design, and location-based services, laying the groundwork for holistically integrating individual interventions for promoting cycling. Next, we present the key contributions of this study.

First, the Spatial Nudging framework summarizes existing but fragmented perspectives to describe nudges in a structured way, as shown in Figure 2, and links existing nudging strategies by introducing a novel concept – Spatial Nudging (refer to Figure 2). The key Spatial Nudging framework characteristic is the role of spatial elements and information within individual nudge strategies. Second, we clarified the role of the physical environment in nudging by highlighting the interaction between perceived affordances, design intent, and choice environments based on links between the Nudge Theory and the Theory of Affordances (refer to Figure 1). Specifically, the framework reinforces the idea that physical interventions designed with a behavioral goal in mind qualify as nudges, advocating for nudging as a deliberate design principle to enhance intervention effectiveness [54]. Third, we have introduced a methodology to support nudges in route choice tasks (see Section 3). This methodology illustrates how graph representation can be used to align both physical infrastructure and digital tools with users' cognitive expectations. We also showcase a novel application of the Cognitive Graph hypothesis in cycling, which is, to our knowledge, the first such case. Finally, although we focus the framework on cycling, it is important to note that it could be adjusted to support sustainable food or energy consumption interventions as they share sustainability goals, require behavioral change, and can be targeted in physical and digital choice environments [31].

Table 5 Shows pairwise distance measures for a sample of trajectories (n=27) in Zurich, comparing the cognitive route (cr) with the trajectory (tr) and the shortest path (sp). The distance measures used include Edit distance, Jaccard distance, and the Longest Common Subsequence (LCS).

Route Pair	Edit distance (±)	Jaccard distance (±)	LCS distance (±)
tr-sp	0.659 (±0.141)	0.716 (±0.14)	0.642 (±0.166)
tr-cr	**0.512** (±0.217)	**0.522** (±0.231)	**0.583** (±0.207)
cr-sp	0.584 (±0.226)	0.666 (±0.201)	0.693 (±0.180)

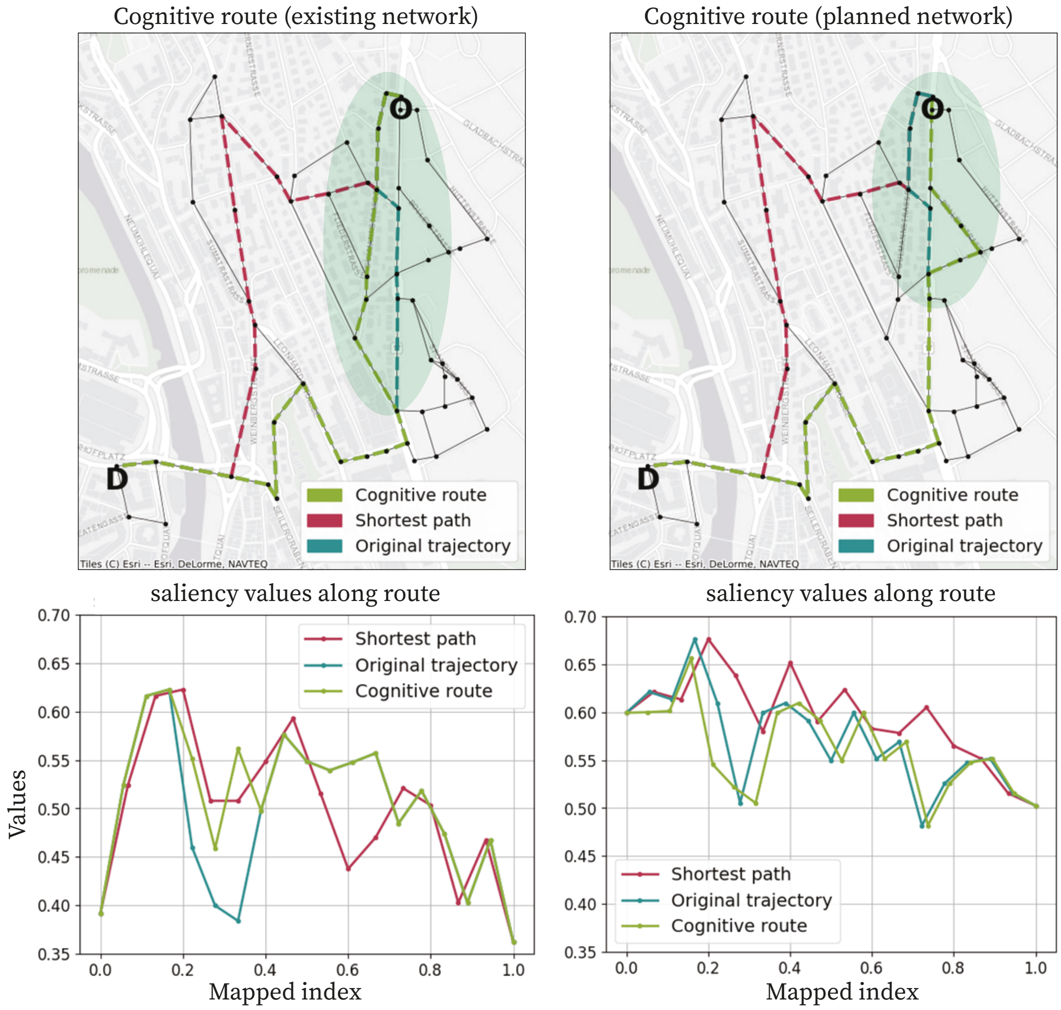

Figure 4 Compares an example trajectory with the generated cognitive route and the shortest path regarding the overall cycling saliency values along each route for the existing and planned bike network scenarios.

We acknowledge several limitations. First, although we have demonstrated how the proposed supportive methodology could advance nudging strategies, it is only the initial conceptualization. We still need to refine and validate each step of the proposed workflow for cycling. This includes comparing cognitive graph generation between different cyclist typologies and between cyclists and pedestrians more generally. Similarly, testing the methodology with a larger set of cycling data across cities of varying sizes and urban morphologies would further validate our initial findings. It is essential to gain empirical evidence from real-world use cases across a range of urban geographies, potentially derived from long-term studies that combine physical and digital interventions, to validate the Spatial Nudging framework. Second, the presented workflow only partially aligns perceived and objective environments in our nudging strategies. This is because we did not consider demographics, attitudes, cycling culture, or city-wide mobility patterns (e.g., peak and off-peak hours) in the proposed workflow. Although we dynamically model perceived affordances at each step of the route planning task, factors like time of day, trip purpose, and level of familiarity certainly influence the internal reasoning behind route choices, warranting further research. Third, while our study focuses on perceived affordances within the primary choice environments (physical and digital) that impact sustainable mobility choices, it also needs to consider other types of affordances, such as motivational, functional, and social-institutional affordances [47], as well as other potential choice environments for active mobility planning like AR. These limitations highlight multiple directions for future research.

Future Work Directions

We see two main future research directions: workflow validation and theoretical framework extension. To validate the cognitive route generation workflow, we will apply it in cities with varying levels of cycling activity, different urban morphologies, and diverse bike network qualities. This approach will enable us to assess the robustness of the workflow across a range of contexts. Integrating physiological data and personalized saliency definitions based on analyzing cyclist-related data can further confirm the metric selection and saliency values. Other known cognitive biases, such as the longest first trip leg or minimal angular deviation, could be integrated and tested with our proposed workflow.

The Spatial Nudging framework can be further extended. For instance, the nudging categories summarized in Figure 2 could be expanded to include *who* the nudges target, such as different types of cyclists. Additionally, while we have illustrated the framework with a use case for the route choice task, further research is required for other critical travel choices, such as mode choice. Furthermore, although many examples exist of AR support in decision-making for tourism and air transport, its potential to nudge toward active mobility has not been explored. Therefore, examining the use of AR (and immersive technologies more generally) to alter the perceived affordances of the physical environment for cycling could expand the range of nudging strategies and choice environments discussed in the framework. Finally, implementing a comprehensive test case that merges physical interventions (such as a new bike lane) with persuasive technologies (mobile trip planner recommendations) could provide concrete validation for our framework.

Conclusions

We present the Spatial Nudging framework that provides a more integrated perspective on nudging in the mobility domain and grounds it as a multifaceted behavioral change strategy. We refine the definition of nudging strategies across physical and digital choice environments by linking behavioral theories related to perception. Furthermore, this paper advocates nudging as a deliberate design principle to enhance the effectiveness of physical or digital interventions. Additionally, we introduce initial steps towards utilizing a graph representation for aligning perceived and objective environments of cycling routes. Through a use case, we demonstrate how the Spatial Nudging framework and the supportive methodology can support nudging interventions to promote sustainable mobility cohesively.

References

1 Rachel Aldred and Katrina Jungnickel. Why culture matters for transport policy: the case of cycling in the UK. *Journal of Transport Geography*, 34:78–87, January 2014. doi:10.1016/j.jtrangeo.2013.11.004.

2 Lukas Ballo and Kay W. Axhausen. Modeling sustainable mobility futures using an automated process of road space reallocation in urban street networks. a case study in zurich. In *103rd Annual Meeting of the Transportation Research Board (TRB 2024); Conference Location: Washington, DC, USA; Conference Date: January 7-11, 2024*, 2024-01.

3 Lukas Ballo, Lucas Meyer De Freitas, Adrian Meister, and Kay W. Axhausen. The E-Bike City as a radical shift toward zero-emission transport: Sustainable? Equitable? Desirable? *Journal of Transport Geography*, 111:103663, July 2023. doi:10.1016/j.jtrangeo.2023.103663.

4 Koen Bandsma, Ward Rauws, and Gert De Roo. Optimising Nudges in Public Space: Identifying and Tackling Barriers to Design and Implementation. *Planning Theory & Practice*, 22(4):556–571, August 2021. doi:10.1080/14649357.2021.1962957.

5 David Banister. Cities, mobility and climate change. *Journal of Transport Geography*, 19(6):1538–1546, November 2011. doi:10.1016/j.jtrangeo.2011.03.009.

6 Tristan Baumann and Hanspeter A. Mallot. Metric information in cognitive maps: Euclidean embedding of non-Euclidean environments. *PLOS Computational Biology*, 19(12):1–14, December 2023. Publisher: Public Library of Science. doi:10.1371/journal.pcbi.1011748.

7 Silvia Bernardi, Lissy La Paix-Puello, and Karst Geurs. Modelling route choice of Dutch cyclists using smartphone data. *Journal of Transport and Land Use*, 11(1), October 2018. doi:10.5198/jtlu.2018.1143.

8 Anna Boldina, Paul H. P. Hanel, and Koen Steemers. Active urbanism and choice architecture: encouraging the use of challenging city routes for health and fitness. *Landscape Research*, 48(3):276–296, April 2023. doi:10.1080/01426397.2022.2142204.

9 Christian Bongiorno, Yulun Zhou, Marta Kryven, David Theurel, Alessandro Rizzo, Paolo Santi, Joshua Tenenbaum, and Carlo Ratti. Vector-based pedestrian navigation in cities. *Nature Computational Science*, 1(10):678–685, October 2021. doi:10.1038/s43588-021-00130-y.

10 Ralph Buehler and John Pucher. *Cycling for sustainable cities.* MIT Press, 2021.

11 Francesca Cellina, Dominik Bucher, Francesca Mangili, José Veiga Simão, Roman Rudel, and Martin Raubal. A Large Scale, App-Based Behaviour Change Experiment Persuading Sustainable Mobility Patterns: Methods, Results and Lessons Learnt. *Sustainability*, 11(9):2674, May 2019. doi:10.3390/su11092674.

12 Francesca Cellina, Dominik Bucher, José Veiga Simão, Roman Rudel, and Martin Raubal. Beyond Limitations of Current Behaviour Change Apps for Sustainable Mobility: Insights from a User-Centered Design and Evaluation Process. *Sustainability*, 11(8):2281, April 2019. doi:10.3390/su11082281.

13 Samuel Chng. Advancing Behavioural Theories in Sustainable Mobility: A Research Agenda. *Urban Science*, 5(2):43, May 2021. doi:10.3390/urbansci5020043.

14 Jerònia Cubells, Carme Miralles-Guasch, and Oriol Marquet. E-scooter and bike-share route choice and detours: Modelling the influence of built environment and sociodemographic factors. *Journal of Transport Geography*, 111:103664, July 2023. doi:10.1016/j.jtrangeo.2023.103664.

15 R. de Groot and vervoer en infrastructuur CROW kenniscentrum voor verkeer. *Design Manual for Bicycle Traffic*. C.R.O.W. record. CROW, 2016. URL: https://books.google.ch/books?id=FMZOtAEACAAJ.

16 Denise De Ridder, Joram Feitsma, Mariëtte Van Den Hoven, Floor Kroese, Thomas Schillemans, Marcel Verweij, Tina Venema, Anastasia Vugts, and Emely De Vet. Simple nudges that are not so easy. *Behavioural Public Policy*, 8(1):154–172, January 2024. doi:10.1017/bpp.2020.36.

17 Jonas De Vos, Tim Schwanen, Veronique Van Acker, and Frank Witlox. Do satisfying walking and cycling trips result in more future trips with active travel modes? An exploratory study. *International Journal of Sustainable Transportation*, 13(3):180–196, March 2019. doi:10.1080/15568318.2018.1456580.

18 Jennifer Dill, Cynthia Mohr, and Liang Ma. How Can Psychological Theory Help Cities Increase Walking and Bicycling? *Journal of the American Planning Association*, 80(1):36–51, January 2014. doi:10.1080/01944363.2014.934651.

19 Rohit K. Dubey, Samuel S. Sohn, Tyler Thrash, Christoph Hölscher, André Borrmann, and Mubbasir Kapadia. Cognitive Path Planning With Spatial Memory Distortion. *IEEE Transactions on Visualization and Computer Graphics*, 29(8):3535–3549, August 2023. doi:10.1109/TVCG.2022.3163794.

20 Aslak Fyhri, Katrine Karlsen, and Hanne B. Sundfør. Paint It Red - A Multimethod Study of the Nudging Effect of Coloured Cycle Lanes. *Frontiers in Psychology*, 12:662679, June 2021. `doi:10.3389/fpsyg.2021.662679`.

21 Marta Garcia-Sierra, Jeroen C.J.M. Van Den Bergh, and Carme Miralles-Guasch. Behavioural economics, travel behaviour and environmental-transport policy. *Transportation Research Part D: Transport and Environment*, 41:288–305, December 2015. `doi:10.1016/j.trd.2015.09.023`.

22 J. J. Gibson. The theory of affordances. In R. Shaw and J. Bransford, editors, *Perceiving, acting, and knowing: Toward an ecological psychology*, pages 67–82. Lawrence Erlbaum Associates, 1977.

23 Ayda Grisiute. Cognitive Route Planning. Software, swhId: `swh:1:dir:5720b0f26f85d4566df66b9fe80d47e111a00a66` (visited on 2024-08-22). URL: `https://github.com/mie-lab/cognitive_route_planning`.

24 Ayda Grisiute, Nina Wiedemann, Pieter Herthogs, and Martin Raubal. An ontology-based approach for harmonizing metrics in bike network evaluations. *under review*, 2024.

25 William Hebblewhite and Alexander James Gillett. Every step you take, we'll be watching you: nudging and the ramifications of GPS technology. *AI & SOCIETY*, 36(3):863–875, September 2021. `doi:10.1007/s00146-020-01098-5`.

26 Gareth J Hollands, Ian Shemilt, Theresa M Marteau, Susan A Jebb, Michael P Kelly, Ryota Nakamura, Marc Suhrcke, and David Ogilvie. Altering micro-environments to change population health behaviour: towards an evidence base for choice architecture interventions. *BMC Public Health*, 13(1):1218, December 2013. `doi:10.1186/1471-2458-13-1218`.

27 Dennis Hummel and Alexander Maedche. How effective is nudging? A quantitative review on the effect sizes and limits of empirical nudging studies. *Journal of Behavioral and Experimental Economics*, 80:47–58, June 2019. `doi:10.1016/j.socec.2019.03.005`.

28 Ole B. Jensen, Ditte Bendix Lanng, and Simon Wind. Mobilities design – towards a research agenda for applied mobilities research. *Applied Mobilities*, 1(1):26–42, January 2016. `doi:10.1080/23800127.2016.1147782`.

29 Daniel Kahneman. *Thinking, fast and slow.* Farrar, Straus and Giroux, New York, 1st ed edition, 2011.

30 Heeseo Rain Kwon and Elisabete A. Silva. Matching Behavioral Theories and Rules with Research Methods in Spatial Planning-Related Fields. *Journal of Planning Literature*, 38(2):245–262, May 2023. `doi:10.1177/08854122231157708`.

31 Matthias Lehner, Oksana Mont, and Eva Heiskanen. Nudging – A promising tool for sustainable consumption behaviour? *Journal of Cleaner Production*, 134:166–177, 2016. `doi:10.1016/j.jclepro.2015.11.086`.

32 Martin Loidl, Dana Kaziyeva, Robin Wendel, Claudia Luger-Bazinger, Matthias Seeber, and Charalampos Stamatopoulos. Unlocking the Potential of Digital, Situation-Aware Nudging for Promoting Sustainable Mobility. *Sustainability*, 15(14):11149, July 2023. `doi:10.3390/su151411149`.

33 Claudia Luger-Bazinger, Guntram Geser, and Veronika Hornung-Prähauser. Digital behavioural interventions for sustainable mobility: A review of behaviour change techniques in mobile apps. In Sampson Alain, editor, *The Behavioral Economics Guide 2023*, pages 68–75. Behavioral Science Solutions Ltd, 2023.

34 Liang Ma and Jason Cao. How perceptions mediate the effects of the built environment on travel behavior? *Transportation*, 46(1):175–197, February 2019. `doi:10.1007/s11116-017-9800-4`.

35 E.J. Manley, S.W. Orr, and T. Cheng. A heuristic model of bounded route choice in urban areas. *Transportation Research Part C: Emerging Technologies*, 56:195–209, July 2015. `doi:10.1016/j.trc.2015.03.020`.

36 Henry Martin, Nina Wiedemann, Daniel J. Reck, and Martin Raubal. Graph-based mobility profiling. *Computers, Environment and Urban Systems*, 100:101910, March 2023. `doi:10.1016/j.compenvurbsys.2022.101910`.

37 Lynn Meuleners, Michelle Fraser, and Paul Roberts. Improving cycling safety through infrastructure design: A bicycle simulator study. *Transportation Research Interdisciplinary Perspectives*, 18:100768, March 2023. doi:10.1016/j.trip.2023.100768.

38 Lucas Meyer de Freitas and Kay W. Axhausen. Cycling potentials in Switzerland: An assessment of its determinants using health survey data and first results. In *22th Swiss Transport Research Conference*, May 2022. doi:10.3929/ETHZ-B-000548622.

39 Stuart Mills. Personalized nudging. *Behavioural Public Policy*, 6(1):150–159, January 2022. doi:10.1017/bpp.2020.7.

40 Robert Münscher, Max Vetter, and Thomas Scheuerle. A Review and Taxonomy of Choice Architecture Techniques: Choice Architecture Techniques. *Journal of Behavioral Decision Making*, 29(5):511–524, December 2016. doi:10.1002/bdm.1897.

41 Mohsen Nazemi, Michael A. B. van Eggermond, and Alexander Erath. Using virtual reality to study bicycle level of service for urban street segments. In *99th Annual Meeting of the Transportation Research Board, Washington, DC, USA, January 12-16, 2020*. Transportation Research Board, 2020. doi:10.3929/ETHZ-B-000356535.

42 Donald A. Norman. *The design of everyday things*. Basic Books, New York, New York, revised and expanded edition edition, 2013.

43 Open source routing machine (osrm). OSRM Project. Accessed: 2024-04-25. URL: http://project-osrm.org/.

44 Pavithra Parthasarathi, David Levinson, and Hartwig Hochmair. Network Structure and Travel Time Perception. *PLoS ONE*, 8(10):e77718, October 2013. doi:10.1371/journal.pone.0077718.

45 Mashrur Rahman and Gian-Claudia Sciara. Travel attitudes, the built environment and travel behavior relationships: Causal insights from social psychology theories. *Transport Policy*, 123:44–54, July 2022. doi:10.1016/j.tranpol.2022.04.012.

46 Martin Raubal, Dominik Bucher, and Henry Martin. Geosmartness for Personalized and Sustainable Future Urban Mobility. In Wenzhong Shi, Michael F. Goodchild, Michael Batty, Mei-Po Kwan, and Anshu Zhang, editors, *Urban Informatics*, pages 59–83. Springer Singapore, Singapore, 2021. Series Title: The Urban Book Series. doi:10.1007/978-981-15-8983-6_6.

47 Martin Raubal and Reinhard Moratz. A Functional Model for Affordance-Based Agents. In Erich Rome, Joachim Hertzberg, and Georg Dorffner, editors, *Towards Affordance-Based Robot Control*, volume 4760, pages 91–105. Springer Berlin Heidelberg, Berlin, Heidelberg, 2008. Series Title: Lecture Notes in Computer Science. doi:10.1007/978-3-540-77915-5_7.

48 Daniel J. Reck, David A. Hensher, and Chinh Q. Ho. MaaS bundle design. *Transportation Research Part A: Policy and Practice*, 141:485–501, November 2020. doi:10.1016/j.tra.2020.09.021.

49 Tim Schwanen, David Banister, and Jillian Anable. Rethinking habits and their role in behaviour change: the case of low-carbon mobility. *Journal of Transport Geography*, 24:522–532, September 2012. doi:10.1016/j.jtrangeo.2012.06.003.

50 Ivana Semanjski, Angel Lopez Aguirre, Johan De Mol, and Sidharta Gautama. Policy 2.0 Platform for Mobile Sensing and Incentivized Targeted Shifts in Mobility Behavior. *Sensors*, 16(7):1035, July 2016. doi:10.3390/s16071035.

51 Alin Semenescu, Alin Gavreliuc, and Paul Sârbescu. 30 Years of soft interventions to reduce car use – A systematic review and meta-analysis. *Transportation Research Part D: Transport and Environment*, 85:102397, August 2020. doi:10.1016/j.trd.2020.102397.

52 Ali Soltani, Andrew Allan, Masoud Javadpoor, and Jaswanth Lella. Space Syntax in Analysing Bicycle Commuting Routes in Inner Metropolitan Adelaide. *Sustainability*, 14(6):3485, March 2022. doi:10.3390/su14063485.

53 Juliet Steffen, Hannah Hook, and Frank Witlox. Improving interest in public, active, and shared travel modes through nudging interventions. *Transportation Research Part F: Traffic Psychology and Behaviour*, 103:353–367, May 2024. doi:10.1016/j.trf.2024.04.020.

54 Cass R. Sunstein. *On Freedom.* Princeton University Press, February 2019. doi:10.1515/9780691192024.

55 Fateme Teimouri, Kai-Florian Richter, and Hartwig H. Hochmair. Analysis of route choice based on path characteristics using Geolife GPS trajectories. *Journal of Location Based Services*, pages 1–27, June 2023. doi:10.1080/17489725.2023.2229285.

56 Richard H. Thaler and Cass R. Sunstein. *Nudge: Improving decisions about health, wealth, and happiness.* Nudge: Improving decisions about health, wealth, and happiness. Yale University Press, New Haven, CT, US, 2008. Pages: x, 293.

57 Francesco Maria Turno and Irina Yatskiv Jackiva. Graph-Based Approach for Personalized Travel Recommendations. *Transport and Telecommunication Journal*, 24(4):423–433, November 2023. doi:10.2478/ttj-2023-0033.

58 Veronique Van Acker, Ben Derudder, and Frank Witlox. Why people use their cars while the built environment imposes cycling. *Journal of Transport and Land Use*, 6(1):53–62, April 2013. doi:10.5198/jtlu.v6i1.288.

59 Loes Van Renswouw, Carine Lallemand, Pieter Van Wesemael, and Steven Vos. Creating active urban environments: insights from expert interviews. *Cities & Health*, 7(3):463–479, May 2023. doi:10.1080/23748834.2022.2132585.

60 Miroslav Vasilev, Ray Pritchard, and Thomas Jonsson. Trialing a Road Lane to Bicycle Path Redesign—Changes in Travel Behavior with a Focus on Users' Route and Mode Choice. *Sustainability*, 10(12):4768, December 2018. doi:10.3390/su10124768.

61 Zhenzhen Wang, Sylvia Y. He, and Yee Leung. Applying mobile phone data to travel behaviour research: A literature review. *Travel Behaviour and Society*, 11:141–155, April 2018. doi:10.1016/j.tbs.2017.02.005.

62 William H. Warren, Daniel B. Rothman, Benjamin H. Schnapp, and Jonathan D. Ericson. Wormholes in virtual space: From cognitive maps to cognitive graphs. *Cognition*, 166:152–163, September 2017. doi:10.1016/j.cognition.2017.05.020.

63 Markus Weinmann, Christoph Schneider, and Jan Vom Brocke. Digital Nudging. *Business & Information Systems Engineering*, 58(6):433–436, December 2016. doi:10.1007/s12599-016-0453-1.

64 Paul Weiser, Simon Scheider, Dominik Bucher, Peter Kiefer, and Martin Raubal. Towards sustainable mobility behavior: research challenges for location-aware information and communication technology. *GeoInformatica*, 20(2):213–239, April 2016. doi:10.1007/s10707-015-0242-x.

65 N. Wiedemann, H. Martin, and M. Raubal. Unlocking social network analysis methods for studying human mobility. *AGILE: GIScience Series*, 3:19, 2022. doi:10.5194/agile-giss-3-19-2022.

66 Jan M. Wiener and Hanspeter A. Mallot. 'Fine-to-Coarse' Route Planning and Navigation in Regionalized Environments. *Spatial Cognition & Computation*, 3(4):331–358, December 2003. doi:10.1207/s15427633scc0304_5.

67 Devon Paige Willis, Kevin Manaugh, and Ahmed El-Geneidy. Cycling Under Influence: Summarizing the Influence of Perceptions, Attitudes, Habits, and Social Environments on Cycling for Transportation. *International Journal of Sustainable Transportation*, 9(8):565–579, 2015. doi:10.1080/15568318.2013.827285.

68 Claudia Yamu, Akkelies Van Nes, and Chiara Garau. Bill Hillier's Legacy: Space Syntax—A Synopsis of Basic Concepts, Measures, and Empirical Application. *Sustainability*, 13(6):3394, March 2021. doi:10.3390/su13063394.

69 Sina Zimmermann, Thomas Schulz, Andreas Hein, Heiko Gewald, and Helmut Krcmar. Motivating change in commuters' mobility behaviour: Digital nudging for public transportation use. *Journal of Decision Systems*, pages 1–27, April 2023. doi:10.1080/12460125.2023.2198056.