

Review

Toward Multimodal Seamless Navigation in Smart Cities: A Critical Review of Positioning, Navigation Data, Route Planning, and Guidance

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Abstract

With the advancement of smart city technologies and the proliferation of Mobility as a Service (MaaS), realizing seamless navigation that continuously connects heterogeneous mobility modes and indoor–outdoor spaces has emerged as a critical challenge. However, existing navigation services operate in a fragmented, siloed manner, segmented by transport mode and spatial environment, and thus possess fundamental limitations in supporting continuous mobility. This study establishes an analytical framework comprising the four core components of navigation systems (positioning, navigation data, route planning, and guidance) and critically reviews 108 prior studies identified through purposive sampling from Web of Science, Scopus, and Google Scholar to evaluate the technical requirements and the level of seamless integration achieved for each component. The analysis reveals that while each component has reached a high level of maturity within its individual domain, four critical technical gaps persist across all components: positioning handover discontinuities at indoor–outdoor transition zones, structural and semantic inconsistencies between heterogeneous spatial datasets, static route planning that fails to account for transition-space uncertainties, and guidance systems whose context resets upon changes in transport mode. These gaps originate not from insufficient performance of individual technologies but from a systematic lack of research at the interface points between components. Overcoming these challenges necessitates a comprehensive redesign of the integrated system architecture, encompassing dynamically adaptive multi-sensor fusion positioning, hierarchical heterogeneous data integration models, probabilistic cost modeling for transition spaces, and adaptive guidance systems based on automatic context handover.



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1. Introduction

Recent advances in smart city technologies and the spread of the Mobility as a Service (MaaS) concept are transforming urban spaces from mere residential areas into complex environments where humans and diverse mobility agents coexist. As illustrated in Figure 1, the emergence of new mobility modes such as autonomous vehicles, delivery robots, and personal mobility devices is maximizing the efficiency of urban travel. At the same time, the coexistence with traditional transport modes (walking, driving, and public transit) is

increasing the complexity of shared physical spaces [1]. In such an environment, a core object of smart city mobility is to optimize travel connectivity [2], and the realization of seamless navigation, defined here as multimodal and uninterrupted navigation across heterogeneous spatial environments and transport modes that provides continuous mobility services without requiring user intervention during transitions between indoor–outdoor spaces or mode changes throughout a journey, is essential [3].



Figure 1. Example of mobility complexity in a smart city (Source: <https://www.hyundaimotorgroup.com/en/tech/CONT0000000000092548>, accessed on 25 June 2026).

However, existing navigation services operate in a fragmented, ‘siloe’d’ manner according to their target users and spatial environments, and thus fail to support continuous user mobility flows. Accordingly, conventional navigation services have evolved independently, each optimized for specific modes such as vehicles or pedestrians [4]. For example, vehicle navigation systems guide users only to the parking entrance of a destination building but do not provide the route to the final destination inside the building. Similarly, public transit or pedestrian applications typically provide route information to a subway exit but often omit detailed paths through complex transfer corridors or after entering a building. Consequently, every time the transport mode changes, users must switch between different navigation services or navigate unguided segments on their own, resulting in a disjointed experience that constitutes a significant barrier to seamless navigation. In addition to the service fragmentation caused by transport mode boundaries, technical discontinuities arising from changes in the physical characteristics of spaces also significantly impede seamless navigation. Outdoor environments with reliable GPS signals and indoor or underground environments where satellite signals are blocked rely on fundamentally different positioning technologies and data construction methods [5,6]. In outdoor settings, 2D maps centered on road networks have become the standard; however, despite the importance of floor-level transitions and three-dimensional structures in indoor environments, no unified data standards or service infrastructure exist. As a result, when a user moves from outdoors to indoors, the navigation service terminates with a ‘destination arrived’ message, leaving the remaining indoor journey unsupported. Ultimately, to realize truly seamless mobility,

it is necessary to comprehensively identify the barriers to seamless navigation service implementation, including both inter-modal and inter-spatial discontinuities, and to adopt an integrated approach that connects heterogeneous systems into a single continuous flow.

Accordingly, this study aims to identify the gaps that must be addressed to implement seamless navigation services and to present the research directions necessary to address them. To this end, the paper follows a three-phase research procedure based on prior study reviews and technical analysis, and the overall research flow is depicted in Figure 2.

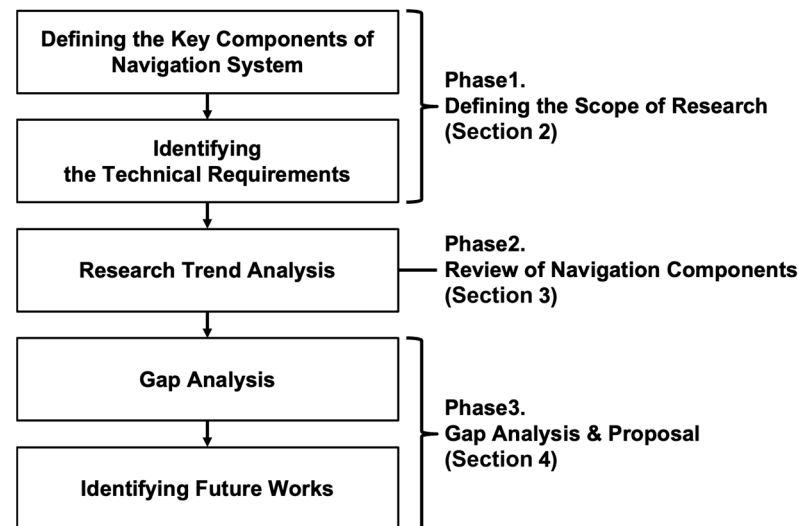


Figure 2. Overview of research methodology and flow.

In the first phase, the architecture of navigation systems is analyzed to define the core components and derive the technical requirements for their implementation. The output of this phase establishes the scope of the study. In the second phase, research trends are analyzed for each navigation system component defined in the first phase. Research trends are examined both in terms of overall developments in individual technology areas and through reclassification from the perspective of seamless navigation service implementation. In the final phase, the results of the prior research analysis are synthesized to identify the gap between current technology and the objectives for seamless navigation implementation. Additionally, specific technical solutions and future research directions for overcoming the identified gaps are proposed.

Based on this methodology, the paper is structured as follows. Section 2 defines the core components constituting a navigation system and derives the technical requirements for each. Section 3 examines overall research trends for each core navigation technology component and reclassifies and analyzes prior studies from the perspective of seamless navigation service implementation. Building on these analyses, Section 4 defines the critical gaps that must be resolved for seamless navigation implementation and proposes specific future research topics to overcome them, and finally, Section 5 discusses the implications and conclusions of this study.

2. Analysis of Technical Requirements for Navigation Service Implementation

Although navigation services take various forms depending on the user and operating environment, the underlying technical architecture can be generalized as a series of information processing steps: ‘determining the current location (Where), understanding the surrounding environment (What), planning the optimal route to the destination (How), and assisting in its execution (Act)’ [3]. Based on navigation-related standards developed by

international standards bodies such as ISO and OGC, along with autonomous driving software stacks from robotics engineering, the technical requirements for navigation systems can be organized into four core components: positioning, navigation data, route planning, and guidance (Figure 3) [7–10]. This section analyzes the technical requirements for each of the four core navigation components to define the scope of this study. Furthermore, by extending the requirements for individual navigation services from the perspective of seamless navigation service implementation, we establish criteria for identifying gaps and proposing future research directions.

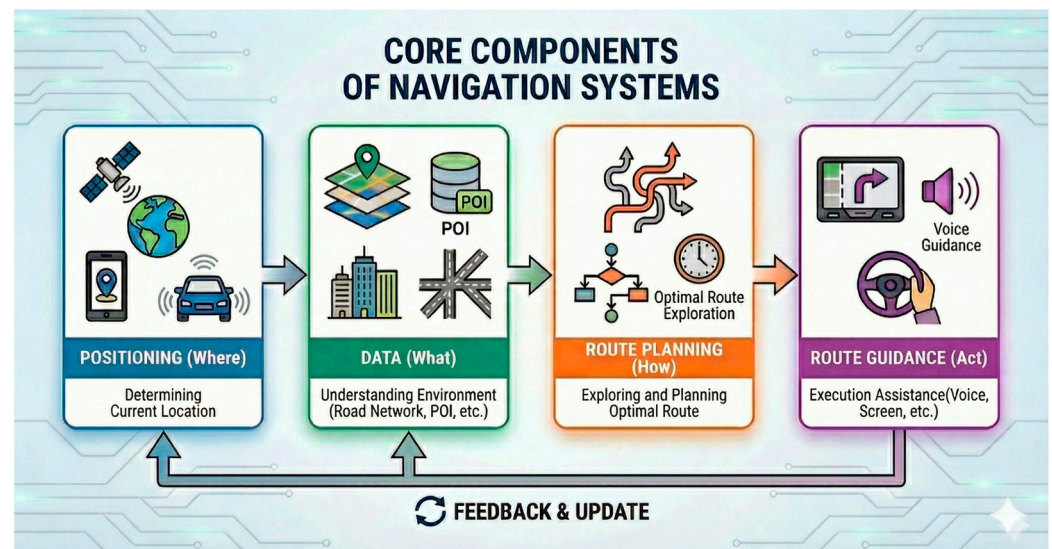


Figure 3. Core components of navigation systems.

2.1. Technical Requirements for Positioning

In navigation systems, positioning refers to the technology that determines the absolute or relative spatial coordinates of a moving object using various sensors and signals. It provides the starting point for route planning and serves as the criterion for determining whether a mobile entity has deviated from the planned route during the guidance phase, making it the most fundamental and critical component of navigation services. In particular, unlike static location determination, positioning in navigation essentially requires continuous location tracking that follows the movement of the mobile entity and real-time performance [11]. Additionally, positioning must be capable of measuring locations across various spatial environments depending on the mobility context. Beyond open outdoor spaces where GNSS reception is reliable, positioning must also function in diverse environments such as tunnels, underpasses, and building interiors [12]. In such GNSS-denied environments, positioning systems inherently rely on pre-deployed infrastructure and its associated datasets (such as Wi-Fi access point layouts, Ultra-Wideband (UWB) anchor positions, and Bluetooth Low Energy (BLE) beacon deployment maps) which are classified under the navigation data component of this study. Furthermore, a minimum level of positioning accuracy must be guaranteed according to service requirements, which may range from several meters to several centimeters depending on the service purpose or function [13,14]. For instance, map-matching techniques, which align raw positioning outputs with reference spatial networks to correct or refine estimated locations, can be employed to enhance location accuracy, illustrating how positioning may draw on navigation data components to meet service-specific accuracy demands [15]. To support uninterrupted navigation services from origin to destination, these positioning-related technical requirements

must operate seamlessly to determine the location of the moving entity even when service environments or contexts change [16].

2.2. Technical Requirements for Navigation Data

In navigation systems, navigation data refer to the foundational elements used to abstract physical mobility spaces into a digital environment for generating routes and conveying information. For the purposes of this study, navigation data encompass structured spatial resources required to support navigation functions, including spatial network data; attribute and semantic data; perceptual and representational data; and dynamic environmental data, while excluding operational log-type data generated during service execution (e.g., user travel records). The detailed classification and analysis of these data types are presented in Section 3.2. Among navigation data, foundational spatial network data used to generate or represent routes (e.g., road networks) require geometric accuracy and topological integrity [17]. Such foundational data must not only accurately represent the physical form of mobility spaces but also ensure that the logical connectivity relationships between points and segments are constructed without errors. Defects in topological structure directly lead to abnormal results in route-finding algorithms, making the assurance of complete network connectivity the most fundamental data requirement. Moreover, rich attribute and semantic data are required for implementing diverse route searches that consider constraints and preferences, as well as for providing detailed route guidance [18]. These elements can be used in different forms for the same object depending on the transport mode or service purpose. For example, stairs may merely impede movement for humans but render movement impossible for unmanned mobile platforms that cannot traverse them. Meanwhile, with the emergence of diverse sensors and advances in computing power, navigation services are increasingly required to go beyond static information-based services and rapidly reflect dynamic real-world changes such as weather variations and events (e.g., accidents, construction) in the mobility space [19]. These requirements may exist in various forms depending on different users or transport modes, and accordingly, data for seamless navigation service implementation require strategies for integrating or linking data that may exist in heterogeneous formats [20].

2.3. Technical Requirements for Route Planning

Route planning refers to the process of computing the optimal travel route from origin to destination. This process requires the definition of origin and destination, as well as a cost function for computing the optimal route between the two points. The cost function may be defined using various variables such as distance, time, cost, and energy efficiency, depending on the transport mode or service objective, and route-finding algorithms must be capable of deriving mathematically optimal solutions that minimize the cost of the defined function. However, when performing route searches over large-scale spaces, fully optimal algorithms can consume excessive computational resources and time due to increased computational complexity. Therefore, in actual service environments, efficient algorithm design is essential to provide users with information without delay—that is, the ability to maintain a balance between search performance and route quality while producing results in real time [21]. Additionally, during route computation, the physical specifications (size, turning radius, etc.) and legal constraints (one-way streets, no-entry zones, etc.) of each transport mode must be strictly incorporated [22], and flexibility must be ensured to immediately detect dynamic environmental changes such as real-time traffic conditions or unexpected road closures, recompute, and present new optimal routes [23]. In particular, when two or more transport modes are used for a journey, deriving an optimization

strategy that balances optimal route computation and search performance at transfer points or spaces where mode changes occur is crucial [24].

2.4. Technical Requirements for Route Guidance

Route guidance refers to the user interface process of conveying the system-determined optimal route to the mobile entity in the form of visual, auditory, or digital signals so that the entity can perceive and execute it. The route guidance information provided must be intuitive to minimize the user's cognitive load and must be delivered at appropriate moments during travel to assist in the entity's decision-making [25]. Furthermore, although guidance may be delivered in different forms depending on the context and navigation scenario, logical consistency and uniformity of the guidance system must be ensured [26]. These route guidance requirements can be provided in various forms in a smart city as environments and transport modes change. For a route guidance system that supports uninterrupted mobility, smooth guidance transitions in such situations are required [27].

2.5. Summary of Technical Requirements from the Seamless Navigation Perspective and Definition of Research Scope

As discussed above, the technical requirements for the four core components of modern navigation systems (positioning, navigation data, route planning, and guidance) have been examined and are summarized in Table 1, distinguishing between the basic requirements for individual navigation service implementation and the extended requirements for seamless navigation service implementation.

Table 1. Summary of technical requirements by core navigation component.

Core Component	Basic Requirements (Individual Navigation)	Extended Requirements (Seamless Navigation)
Positioning	Real-time continuous location tracking Capability across diverse spatial environments Accuracy appropriate to service purpose	Minimized positional error and guaranteed continuity at indoor–outdoor and heterogeneous environment transition zones
Navigation Data	Geometric accuracy and topological integrity Rich attribute and semantic information Representation of dynamic changes	Integrated data modeling for heterogeneous spaces and transport modes
Route Planning	Optimization of cost functions; Computational efficiency for large-scale searches Route computation considering physical and qualitative constraints Reflection of real-time dynamic environmental changes	Optimization of transfer weights and integrated cost functions for multi-modal coordination
Route Guidance	Intuitive guidance provision Timely information delivery Logically consistent and unified guidance system	Adaptive UI/UX transitions based on mobility context awareness

The basic and extended requirements derived for the four core technology components of navigation services serve as a critical evaluation framework for defining the essence of seamless navigation and rigorously identifying research gaps to be overcome. Existing commercial navigation systems and related studies have primarily focused on achieving ‘basic requirements’ aimed at service provision within a single transport mode and homogeneous spatial network. However, in the future mobility environment where multiple transport modes (pedestrians, autonomous vehicles, and even UAM) are interconnected in complex ways, such individual and disconnected technological approaches alone cannot ensure a continuous user experience from a door-to-door perspective. Therefore, satisfying the requirements for seamless navigation, including seamless integration of heterogeneous spatial and mobility data, uninterrupted positioning across indoor–outdoor transition zones, route optimization that minimizes inter-modal transfer friction, and smooth guidance transitions responsive to changes in user mobility context, is an essential.

To enable systematic assessment of implementation progress, specific operational indicators for seamlessness can be defined. These include: (1) route continuity rate: the proportion of inter-modal transition points at which route calculation proceeds without interruption (e.g., $\geq 90\%$) [28,29]; (2) modality switching latency: the elapsed time from mode-change detection to updated guidance display (e.g., ≤ 3 s) [30]; (3) positioning accuracy at handover points: the horizontal error tolerance at system boundary transitions (e.g., 5–10 m outdoor, ≤ 5 m indoor) [31]; and (4) information consistency score: the proportion of waypoint data that remain coherent across subsystem boundaries (e.g., $\geq 90\%$) [32]. Establishing these criteria provides a measurable basis for evaluating the degree of seamlessness achieved by candidate architectures. These values are illustrative examples rather than empirically validated thresholds; precise, standardized values for each indicator remain an open task for future research. It should be noted that these indicators are introduced as a conceptual evaluation framework rather than applied within the component-wise literature analysis conducted in Section 3; their systematic application to the reviewed studies is identified here as a priority direction for future evaluation research.

3. Analysis of Research Trends Related to Seamless Navigation by Navigation Technology Components

In the preceding Section 2, the four core components constituting navigation systems were defined and their technical requirements were examined. In this section, overall research trends for each technology component are reviewed, and prior studies are re-classified and analyzed in depth specifically from the perspective of seamless navigation service implementation.

This study adopts a critical review methodology, in which literature selection is guided by purposive sampling, a deliberate selection of studies that are directly pertinent to the research questions, rather than by exhaustive retrieval. This approach is consistent with the objectives of a critical review, which aims to synthesize and evaluate the state of knowledge in a field through expert judgment rather than to produce a statistically representative sample of all available literature. This approach, however, carries two methodological implications. First, because the number of candidate studies initially retrieved and subsequently excluded was not systematically tracked, the precise replicability of the selection process is limited. Second, the expert-guided nature of purposive sampling introduces the possibility of selection bias, which is acknowledged here as an inherent characteristic of critical review methodology rather than a defect specific to this study.

As shown in Figure 4, the literature search was conducted using Web of Science, Scopus, and Google Scholar as primary databases. Search terms centered on the four core navigation components were applied either individually or in combination, including

‘seamless navigation,’ ‘indoor–outdoor positioning,’ ‘multimodal route planning,’ ‘navigation data model,’ and ‘context-aware guidance,’ with coverage limited to English-language publications from 2010 onward.

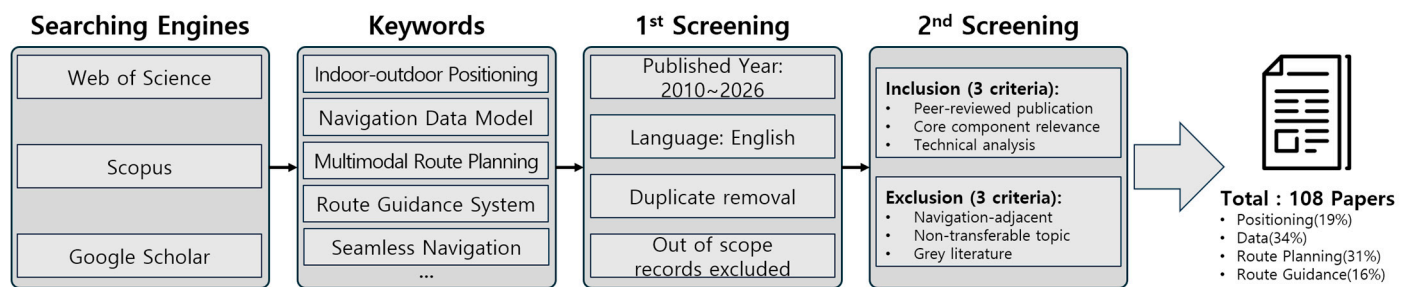


Figure 4. Overview of related research analysis.

Studies were screened by title and abstract against the following explicit criteria. For inclusion, a study was required to: (1) be published in a peer-reviewed journal or conference proceedings; (2) address at least one of the four core navigation components defined in Section 2; and (3) present empirical implementation, experimental evaluation, or substantive technical analysis with direct relevance to navigation in smart city or indoor–outdoor transition environments. Studies were excluded if they: (1) addressed navigation-adjacent topics without direct technical bearing on the defined components (e.g., general smart city policy or infrastructure planning); (2) focused on domain-specific applications with no transferability to seamless navigation contexts; or (3) represented grey literature, technical reports, or non-peer-reviewed documents. A total of 108 papers satisfying these criteria were selected for analysis in this study.

The 108 selected papers were classified according to the four core navigation components defined in this study, and the classification distribution is presented in Table 2. The distribution comprises 20 positioning-related studies (19%), 36 data-related studies (34%), 33 route planning-related studies (31%), and 17 guidance-related studies (16%). The relatively higher proportion of data and route planning studies reflects the fact that heterogeneous spatial data integration and multi-modal route planning represent key technical challenges where recent research activity has been concentrated for seamless navigation implementation.

Table 2. Distribution of cited papers.

Core Component	Sub-Classification	Number of Papers
Positioning	Overview of positioning technologies	10
	Indoor/outdoor handover	5
	Multi-sensor fusion	6
	Subtotal	21
Navigation Data	Overview of data types	15
	Spatial data models	9
	Heterogeneous data linkage and integration	5
	Agent-specific semantics	7
	Subtotal	36

Table 2. Cont.

Core Component	Sub-Classification	Number of Papers
Route Planning	Overview of route planning types	17
	Transition-space route planning	6
	Route weighting and optimization	10
	Subtotal	33
Route Guidance	Overview of guidance types	6
	Cognition- and visualization-based guidance	8
	Instruction- and control-based guidance	4
	Subtotal	18
Total		108

3.1. Analysis of Positioning-Related Research Trends

Diverse positioning technologies have been developed for navigation, classified by signal source and processing method into four types, as shown in Figure 5. GNSS provides absolute outdoor positioning (GPS, Galileo, GLONASS, BeiDou), though accuracy can degrade in dense urban areas [33]. Where satellite signals are unavailable (indoor, underground, or tunnel environments), wireless signal-based methods using cellular (LTE/5G), Wi-Fi, UWB, and Bluetooth beacons are used [5,34,35]. Vision- and sensor-based approaches, including Visual Positioning Systems and LiDAR-based SLAM, enable positioning where neither GNSS nor wireless signals are available [36], while dead reckoning using accelerometers and gyroscopes maintains short-term continuity during indoor–outdoor transitions [37]. On mobile devices, sensor fusion across GNSS, Wi-Fi, Bluetooth, and cellular signals is processed at the OS level and exposed via APIs, including mobility-state context (e.g., stationary, walking, vehicular) for refined navigation services [38]. Beyond these individual domains, research has also pursued fusing them for continuous positioning across diverse environments [39,40], complemented by map-matching techniques that refine raw positioning outputs against reference spatial networks such as road data [15]. As seamless navigation requires continuous positioning across environment transitions, the following subsections analyze this research in detail.

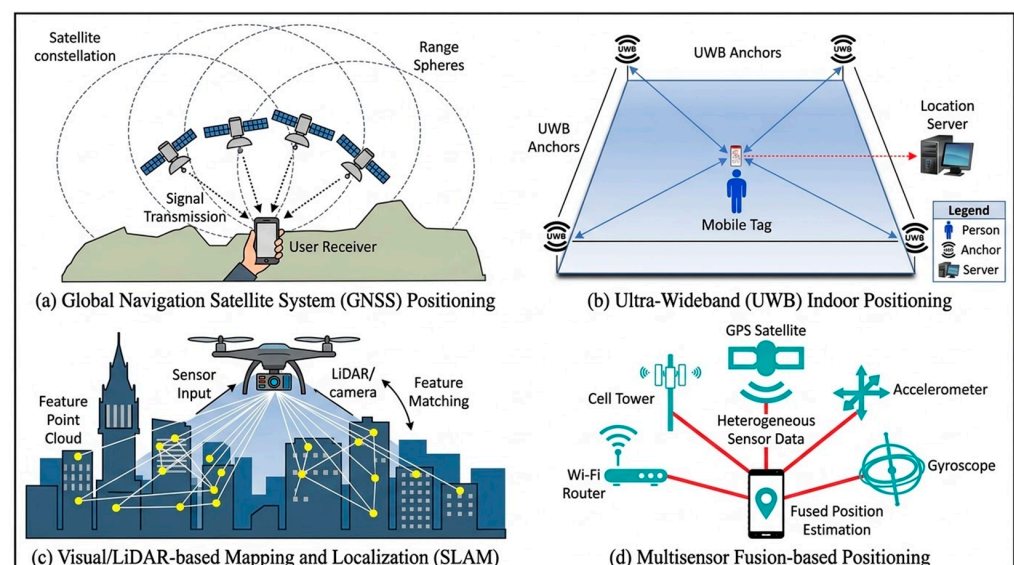


Figure 5. Classification of navigation positioning technology types.

3.1.1. Research on Indoor–Outdoor Environment Transition and Handover Positioning Technologies

Uninterrupted positioning during environment transitions is an essential requirement for seamless navigation [41]. Prior research addressing the discontinuity and error amplification at GNSS–wireless transition zones falls into two categories. The first concerns transition detection: machine learning analysis of sensor variation patterns (illumination, magnetometer, barometer) and GNSS SNR attenuation enables millisecond-level boundary detection, allowing proactive positioning–infrastructure switching [28,42]. The second concerns continuous handover algorithms: to overcome discontinuity from hard handover, dead reckoning (DR) or pedestrian dead reckoning (PDR) are used as a bridging technology [43], with extended Kalman or particle filters fusing PDR data across the transition to ensure trajectory continuity [44].

3.1.2. Research on Positioning Enhancement Through Multi-Sensor Fusion

Since no single positioning technology guarantees accuracy and continuity across all spaces, multi-sensor fusion has been studied as a core technology for seamless positioning [45]. Traditional approaches center on probabilistic estimation via extended Kalman or particle filters, with tight-coupling architectures minimizing IMU drift error during GNSS outages [12,16]; such raw-data-level fusion improves availability even where visible satellites drop below four. More recently, machine learning and deep learning have been applied to dynamically weight sensor reliability as conditions change, overcoming the limitations of conventional filter models [46]. Beyond centralized architectures, federated learning frameworks now enable collaborative positioning-model training across distributed users without centralizing sensitive location data, achieving near-centralized accuracy while preserving privacy [47,48], with transfer-learning variants further reducing the per-site training data needed in new environments, an emerging direction for scalable seamless positioning.

3.2. Analysis of Navigation Data-Related Research Trends

Navigation data abstract real-world spaces into forms interpretable by route-finding and guidance systems. While road networks and POI data have traditionally served vehicle navigation [49,50], the expansion of mobile entities and spatial scope now demands increasingly diverse and precise data forms [51], analyzed below across four tiers. First, data defining traversable areas and connectivity are essential for route planning: link-node road networks serve vehicle, pedestrian, bicycle, and autonomous-vehicle navigation, as shown in Figure 6 [52–54], while mesh or voxel-based representations support pedestrians and robots in lane-free spaces such as plazas and lobbies [55]; vertical connectivity data (entrances, elevators, escalators) support seamless floor-level transitions [56]. Second, data representing spatial attributes and semantics have been studied [57,58]: POI data support place search via name, address, and category [59]; robots require attribute data such as floor material and trafficability [60]; and the concept of ‘destination’ extends beyond entrances to parking areas, bicycle racks, and task-specific positions such as loading docks [50]. Third, data for visual or machine perception of surroundings include 2D/3D maps and satellite imagery for human users [61], and point clouds, HD maps, and occupancy grids for autonomous vehicles and robots [62]. Fourth, beyond these static types, dynamic data layering real-time conditions (traffic volumes, indoor congestion, elevator status, door states) supports route computation that goes beyond simple shortest-path calculation [63]. Existing research thus integrates connectivity-defining network models, semantic attributes, perceptual shape data, and real-time dynamic data toward optimal mobility services; the following subsections analyze this research from the seamless-implementation perspective.

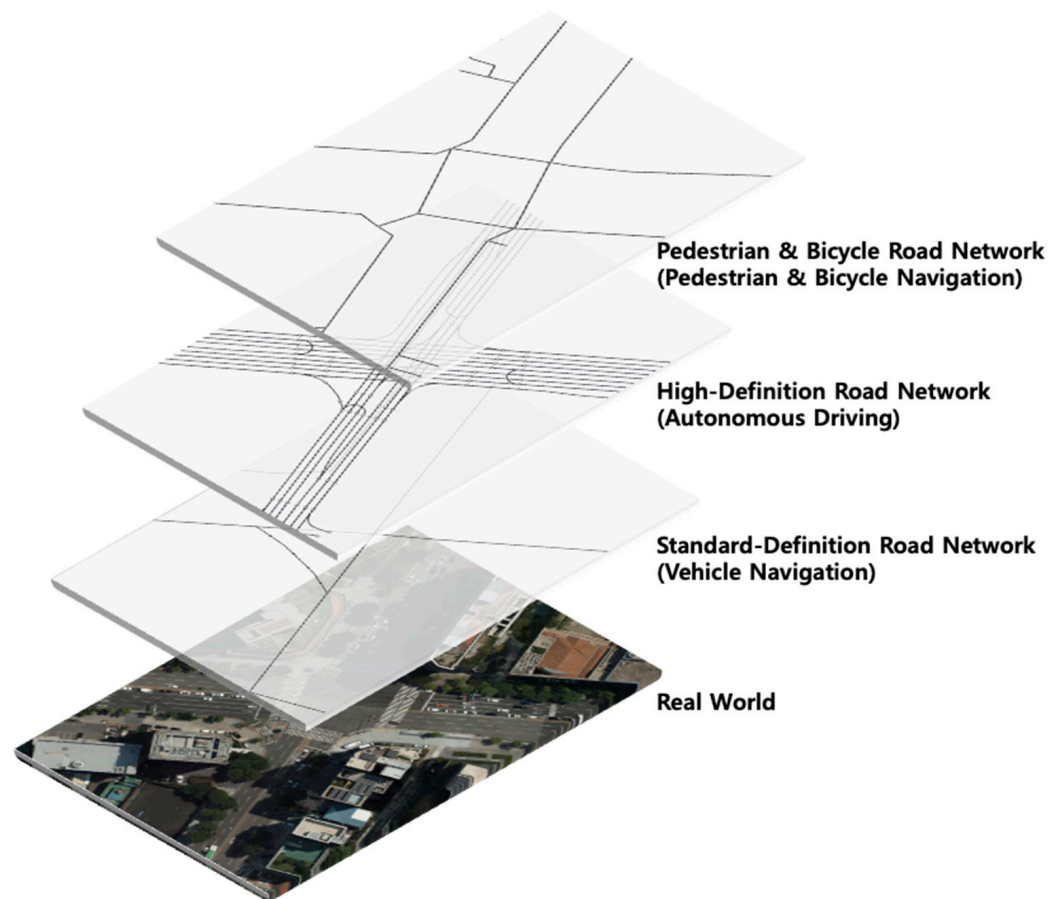


Figure 6. Examples of diverse ‘road’ network data types by transport mode.

3.2.1. Research on Data Models for Representing Diverse Spatial Environments

Data modeling approaches differ by spatial characteristics and entity behavior. Ground-level outdoor research has concentrated on network-centric modeling, abstracting constrained vehicle and pedestrian paths into node-link graphs [64], reflected in standards such as GDF and NDS. By contrast, aerial outdoor and indoor spaces are three-dimensional open spaces without fixed paths, leading research toward geometric modeling using cells or voxels rather than links [65]; ref. [66] further emphasized topological models based on spatial adjacency for complex indoor structures, a structure also adopted by OGC IndoorGML [67]. Beyond space-level models, object-level representation has also been pursued [68], including HD road maps [69] and CityGML for urban components [70]. In the indoor domain, Building Information Modeling (BIM) provides semantically rich object-level data, and recent work extends static BIM into digital twins supplying live semantic data for autonomous indoor navigation and robot path planning [71,72], with extensions to heterogeneous multi-robot planning via shared, weighted BIM-derived connectivity graphs. A persistent limitation, however, is the discrepancy between as-designed BIM models and the dynamic as-built environment, constraining reliability without continuous real-time synchronization. Because such diverse, structurally inconsistent data models coexist, achieving seamless navigation across ground-to-air and outdoor-to-indoor transitions requires linking and integrating these heterogeneous data, the focus of the following subsection.

3.2.2. Linkage and Integration of Heterogeneous Data

Because network, volumetric, and object-based models differ fundamentally in structure, technology for linking or integrating them into a single continuous system is essential for seamless navigation. Research has progressed from defining physical connection points toward structurally unifying data management: anchor nodes or gateways mapping outdoor road-network endpoints to indoor entry points represent the most basic integration stage [29,73,74], though simple point-to-point connections cannot carry attributes such as passability for volumetric entities like robots, motivating extended spatial-representation connections [75]. Other research structurally unifies grid or volumetric spaces by converting them into network formats processable by existing navigation engines, either before route generation or by converting only the resulting route for display [76].

3.2.3. Definition of Agent-Specific Attributes and Semantics

Spatial data in seamless navigation must support different mobile entities in interpreting and interacting with space according to their specific requirements. For human mobility, research has encoded cognitive characteristics, physical constraints, and psychological preferences: landmark elements provide intuitive, reliable information [77–79], while [80] quantified mobility-impeding factors for people with reduced mobility, reflecting the importance of contextual usability for human-oriented services. For unmanned platforms, research has instead focused on semantic information matched to sensor perception and physical constraints: ref. [81] combined real-time SLAM with deep-learning object recognition to construct ‘semantic maps’ enabling robots to execute commands such as ‘go to the chair’; ref. [82] classified semantic mapping technologies by tier; and [83] proposed a semantic model enabling robots to recognize human personal space and observe social navigation norms.

3.3. Analysis of Route Planning-Related Research Trends

Route planning computes the optimal route minimizing travel cost (distance, time, energy). While graph-based search has predominated for structured vehicle road networks [84,85], the diversification of mobile entities and operating environments has driven research into robot navigation in unstructured spaces and schedule-dependent public transit routing [86,87], summarized below by operating environment, as shown in Figure 7. First, network-based pathfinding (Dijkstra’s algorithm and the heuristic-driven A* algorithm [88,89]) serves vehicle and outdoor pedestrian navigation, with Contraction Hierarchies (CH) pre-contracting nodes to achieve real-time performance over national-scale networks in commercial systems [90,91]; for schedule-based public transit, where cost varies with arrival time rather than fixed distance, Time-Dependent Dijkstra and more recent timetable-scanning algorithms such as the Connection Scan Algorithm (CSA) and RAPTOR have become core technologies for large-scale LBS platforms [30,92]. Second, for unstructured spaces such as plazas and lobbies, grid-based discretization with A* has been limited by memory inefficiency and unnatural angular paths [93,94], prompting any-angle techniques such as Theta* [95] and navigation meshes abstracting indoor structures into convex polygons for pedestrians and service robots [96,97]; for high-degree-of-freedom 3D spaces such as UAM and environments with dynamic obstacles, sampling-based algorithms such as RRT* are applied for their probabilistic completeness [22,98].

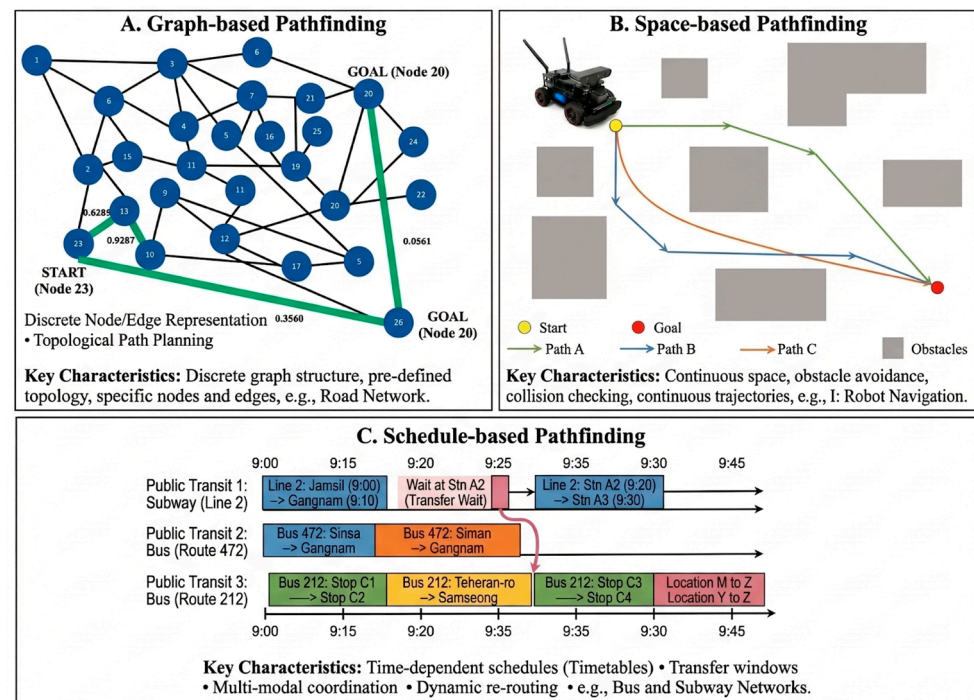


Figure 7. Examples of graph-based, space-based, and schedule-based pathfinding.

3.3.1. Research on Route Planning Considering Transition Spaces

A core challenge of seamless navigation is resolving discontinuities between networks of different topological structure, motivating route planning research focused on continuity in transition spaces. Hybrid graph models establish entry points as anchor or gateway nodes connecting two networks; ref. [3] presented a data model and pathfinding method for indoor–outdoor transition spaces, while [6,99] addressed vertical transition elements such as stairs and elevators in multi-story buildings. A second transition type occurs during transfers between transport modes: studies have considered transfers between public transit modes such as buses and subways [100,101], and [102] proposed an integrated pathfinding method based on ‘reachable time zones’ and ‘action points’ combining static public transit with flexible carpooling networks.

3.3.2. Research on Route Weighting and Optimization

Route weighting and optimization determine the quality of the computed optimal route through cost-function design and efficient solving algorithms tailored to each domain. Route weights have expanded from early shortest-distance or minimum-time formulations toward multi-objective optimization: for vehicles, walking, and public transit, weights incorporate road grades and fares [103], increasingly enhanced with real-time information [104,105]; for autonomous robots, weighting incorporates obstacle detection and avoidance [106,107] and battery/efficiency constraints [108,109]. For computational efficiency, large-scale vehicle and transit networks rely on hierarchical contraction and hub-labeling techniques to accelerate Dijkstra’s and A* algorithms [110,111], while robots and drones navigating high-dimensional unstructured spaces use sampling-based optimization such as RRT* and PRM [112].

3.4. Analysis of Route Guidance-Related Research Trends

Route guidance provides behavioral instructions or control commands that enable a mobile entity to reach its destination and can be broadly categorized into instruction-oriented guidance (directing specific behaviors) and perception-oriented

guidance (explaining surrounding conditions) [113–116]. Traditional turn-by-turn guidance directs vehicles at intersections, requiring precise map matching and carefully timed cues to minimize cognitive load [113,114]; in transit and indoor pedestrian contexts, guidance instead signals mode changes or floor transitions (e.g., ‘Transfer to Line 2’) [115]. In open spaces without defined paths, landmark-based guidance leverages visually perceptible objects (e.g., ‘Enter via the entrance next to Starbucks’) for greater intuitiveness as shown in Figure 8 [116]. Critically, each paradigm is designed for a specific spatial and mobility context, with no established mechanism for coordinating behavioral continuity as a traveler’s context shifts; for example, from vehicular travel to indoor pedestrian navigation to an open plaza; requiring a managed handoff between guidance modalities that conventional architectures do not explicitly address. Extending to robots, instruction-based guidance is distinguished between quantitative control (coordinates, steering angles) [117] and perception-based control (recognition of surrounding objects) [118], reflecting a deeper architectural divide: human-facing guidance manages perceptual ambiguity and cognitive load, while machine-facing guidance ensures deterministic command execution. As autonomous vehicles and pedestrians increasingly share transition spaces such as multimodal interchanges, this divide itself becomes a potential barrier to seamless navigation.



Figure 8. Example of landmark-based route guidance.

3.4.1. Research on Cognition- and Visualization-Based Guidance

The core challenge in human-facing route guidance research is minimizing cognitive load while providing intuitive direction in complex smart-city environments. Beyond conventional turn-by-turn instructions, studies have explored landmark-based guidance [26,119]; AR overlays via smartphones, smart glasses, or vehicle HUDs [120,121]; and multimodal voice/vibration interfaces for users with reduced mobility [31]. Adaptive guidance that adjusts map detail and timing to spatial scale has also been studied [32], though such adaptation typically operates within a single continuous spatial domain rather than coordinating guidance across an indoor–outdoor boundary. More recently, LLM-based systems have enabled conversational, context-aware guidance, interpreting vague queries and sustaining dialogue using route-context metadata [122,123], but remain dependent on pre-constructed indoor maps and dedicated localization infrastructure, limiting their extensibility to seamless cross-domain navigation.

3.4.2. Research on Instruction and Control

For autonomous vehicles and robots, route guidance functions as executable commands and infrastructure communication rather than cognitive understanding [124]. Reference [125] reviewed cooperative perception and control between intelligent infrastructure and autonomous vehicles, framing infrastructure as a primary control agent.

Reference [126] combined global route guidance with reinforcement-learning-based local control for robot navigation in dynamic environments, while reference [127] showed that speed-density-based central route guidance is essential for preventing UAM system deadlocks under demand imbalance. These studies advance guidance precision within clearly bounded domains (cooperative corridors, robot-traversed buildings, or UAM airspace) but each assumes a homogeneous mobility context throughout, leaving guidance handoff at domain boundaries unaddressed.

Taken together, the findings from Sections 3.4.1 and 3.4.2 indicate that route guidance research has advanced within individual modal and spatial contexts, but guidance at modal transition points (the coordinated management of continuity, modality switching, and instruction as a traveler shifts between environments or mobility modes) remains a largely unexplored gap with direct implications for seamless navigation.

3.5. Integrated Analysis of Research Trends

The analysis conducted in Sections 3.1–3.4 confirms that prior studies have achieved considerable progress across each of the four core navigation technology components: positioning, navigation data, route planning, and route guidance. In the positioning domain, GNSS-, wireless signal-, and vision/sensor-based localization technologies have each been advanced to a high degree of maturity. In the data domain, a wide range of spatial data models has been established, spanning road networks, IndoorGML, and CityGML. In route planning, algorithms such as A*, Contraction Hierarchies (CH), and RAPTOR have reached commercial deployment levels, while in route guidance, diverse instruction paradigms including turn-by-turn, landmark-based, and augmented reality (AR) guidance have been proposed. However, when evaluated against the extended requirements for seamless navigation defined in Section 2; specifically, the capacity to simultaneously support transitions across heterogeneous spatial environments and multi-modal mobility; three recurring structural limitations emerge across the reviewed literature.

1. The majority of studies focus on systems optimized for a single condition, whether vehicle or pedestrian, outdoor or indoor, human or robot. As reflected in the Y-axis classifications of Table S2 (Supplementary Materials), 85 of the 108 reviewed papers (78.7%) are assigned a Low or Low-Medium Y-axis level, indicating that cross-modal or cross-environment integration is either not attempted or not a primary research objective. The remaining 23 papers (21.3%) address cross-modal integration as an explicit objective, yet none achieve the system-level implementation required for a High Y-axis classification.
2. Although the four core components have each advanced independently, research addressing the interfaces between them, particularly transition zones, remains comparatively sparse. Of the 13 clusters in Table S2 (Supplementary Materials), only three explicitly target cross-environment or cross-modal transitions as their primary research objective (Sections 3.1.1, 3.2.2 and 3.3.1), collectively comprising 16 papers (14.8% of the corpus). Notably, these three clusters are also the only ones approaching the Seamless Navigation Service Level zone in Figure 9, confirming that transition-focused research constitutes both the most directly relevant and the most underrepresented strand of the reviewed literature.
3. A prevailing practice of static optimization is observed, in which dynamically varying conditions such as dwell time in transition spaces or shifts in mobility context are treated as fixed costs or simplified parameters. Within the route planning component, which accounts for 33 of the 108 reviewed papers, Section 3.3 (Route planning overview, $n = 17$) and Section 3.3.2 (Route weighting and optimization, $n = 10$) are classified at a Low-Medium Y-axis level in Table S2 (Supplementary Materials), reflecting

that multi-modal weighting is partially addressed but without transition-space uncertainty as an explicit modeling target. Only Section 3.3.1 ($n = 6$, 18.2% of route planning papers) explicitly incorporates transition-space variability into its route cost formulations, while the remaining 27 papers (81.8%) apply deterministic cost functions that do not capture the stochastic nature of transition-space dwell times.

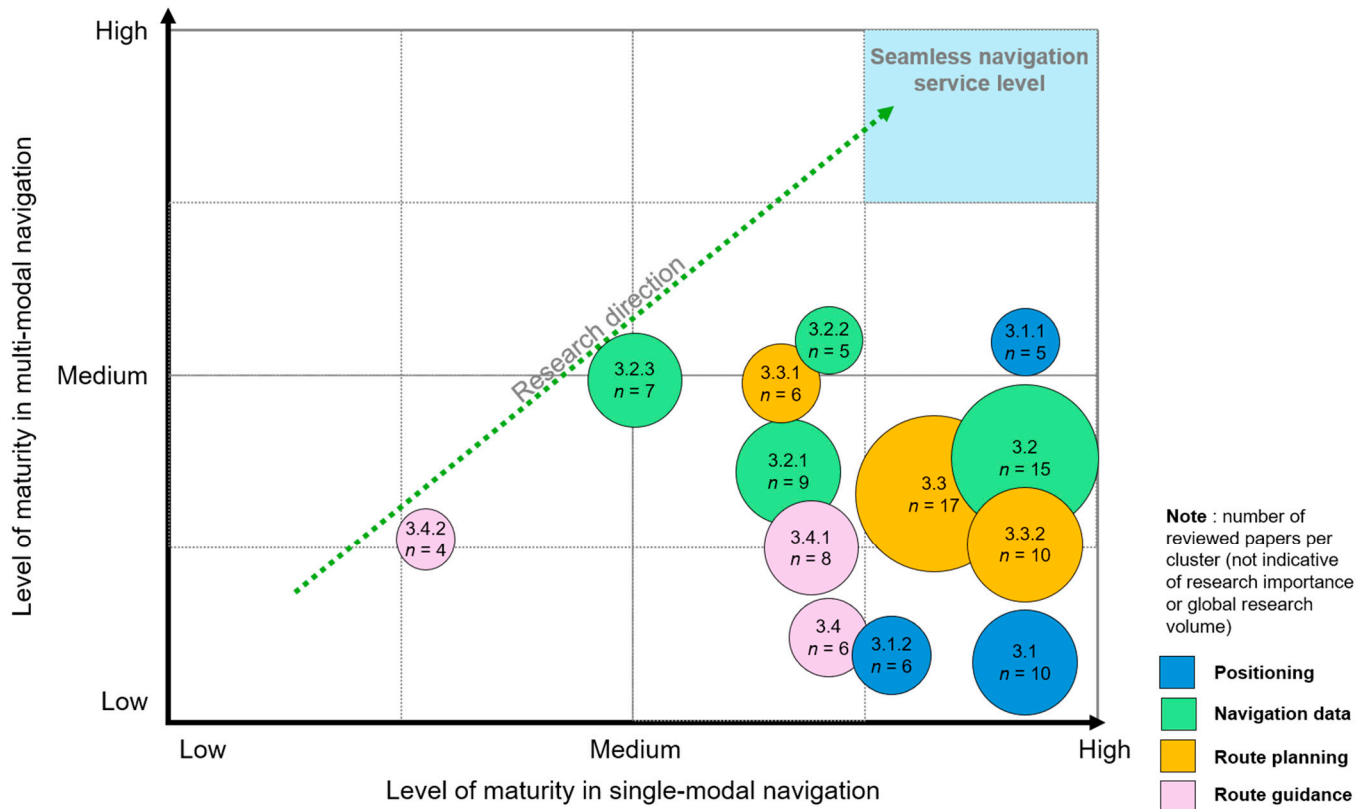


Figure 9. Distribution of reviewed literature clusters by single-modal and multi-modal navigation maturity.

To visualize these tendencies, the reviewed studies are organized into subsection-level clusters and positioned along two axes in Figure 9. The X-axis represents the level of maturity of single-modal navigation in each technology domain, assessed based on the state of commercial deployment and international standardization of the relevant single-modal techniques. The Y-axis represents the level of multi-modal integration maturity, assessed conjunctively by two conditions: whether cross-modal or cross-environment integration constitutes the explicit research objective of the cluster, and whether system-level implementation of such integration has been demonstrated. The operational definitions for each level of both axes are provided in Table 3. The shaded upper-right zone, labeled ‘Seamless Navigation Service Level’, represents the target state in which both axes simultaneously reach a high level, signifying that a technology cluster has achieved high single-modal maturity and demonstrated system-level cross-modal integration. Bubble size is proportional to the number of papers reviewed per subsection and is not intended to represent the relative importance of each research area or the total volume of global research on the topic. Color distinguishes the four core technology components: blue for positioning, green for navigation data, orange for route planning, and pink for route guidance. The positioning rationale for each cluster is provided in Table S2 (Supplementary Materials).

Table 3. Operational definitions for axis levels used in Figure 9.

Level	X-Axis: Single-Modal Navigation Maturity	Y-Axis: Multi-Modal Integration Maturity
Low	Fundamental methods remain at early/experimental stage; limited standardization, minimal commercial deployment.	Research confined to single-modal/single-environment; no cross-modal integration attempted.
Medium	Methods established in specific domains with partial standardization and commercial deployment; universal applicability not yet achieved.	Cross-modal integration is explicit research objective, but system-level implementation not yet fully demonstrated.
High	Reached international standardization or global commercial infrastructure status with broad adoption.	Cross-modal integration is primary contribution AND system-level implementation has been demonstrated.

Intermediate levels (Low-Medium, Medium-High) are used in Table S2 (Supplementary Materials) to indicate transitional positions between the defined anchor points above.

As Figure 9 illustrates, most clusters sit high on the X-axis but low or low-medium on the Y-axis: research has concentrated on advancing single-modal performance without achieving cross-modal system-level integration. The largest literature concentrations (Section 3.3, Section 3.2 ($n = 15$), and Section 3.3.2 ($n = 10$)) are paradoxically the furthest from achieving seamless navigation applicability on the Y-axis. No cluster occupies the upper-right Seamless Navigation Service Level zone defined in Table 3. The closest approaches (Sections 3.1.1, 3.2.2 and 3.3.1) reach only a medium Y-axis level, having adopted cross-modal integration as an explicit objective without full system-level demonstration; the remaining clusters address cross-modal considerations only partially or not at all.

That the Seamless Navigation Service Level zone remains entirely unoccupied, across all four technology components, is itself a central finding: the gap is systemic rather than confined to a single domain. Advancing single-domain performance alone is therefore insufficient; a shift toward an integrative research perspective prioritizing system-level connectivity and continuity is essential. Section 4 builds on these findings to define the critical technology gaps for each core component and propose corresponding research directions.

4. Gap Identification and Future Research Directions for Seamless Navigation Implementation

As confirmed through the analysis in Section 3, current navigation technologies exhibit a high level of technical maturity within each domain, such as outdoor and indoor, or vehicular and pedestrian. However, the seamless navigation envisioned by smart cities cannot be achieved through the advancement of individual technologies alone. The current technical limitations originate not from performance deficiencies in single domains but from the absence of connectivity and interoperability between different domains. Specifically, the integrated analysis in Section 3.5 identified three recurring structural limitations across the reviewed literature: a pervasive single-condition optimization bias, a comparative scarcity of research addressing the interfaces between components, particularly at transition zones, and a prevailing practice of static optimization that treats dynamically variable conditions as fixed parameters. These structural limitations, when evaluated against the extended technical requirements for seamless navigation defined in Section 2, reveal concrete gaps that have remained unresolved across all four core technology components. Accordingly, this section systematically identifies these technical gaps for each component

(positioning, navigation data, route planning, and route guidance) analyzes the causes of service discontinuity arising from information system disconnections despite the physical continuity of spaces, and proposes future research directions to overcome them.

4.1. Positioning-Related Technical Gap Analysis and Future Research Directions

As discussed previously, positioning technologies based on satellite navigation, wireless networks, and inertial/vision sensors have advanced substantially within their respective environments, yet two critical gaps remain for seamless navigation. First, positional discontinuity and delay occur at indoor–outdoor transition zones: hard handover between heterogeneous positioning systems at GNSS shadow boundaries causes positional jumps and service delays, and although soft-handover attempts using context awareness or dead reckoning exist [28,42–44], generalizable transition models robust to diverse movement speeds and complex topologies remain insufficient. Second, sophisticated multi-sensor and deep-learning fusion models [12,16,46] guarantee high accuracy but impose heavy computational and battery burdens on resource-constrained edge devices, while fragmented indoor infrastructure density (e.g., Wi-Fi APs, beacons) makes nationwide continuity difficult to guarantee.

Addressing these gaps requires a paradigm shift from improving absolute positional accuracy within fixed environments toward securing proactive recognition of environmental change and dynamic adaptability. For the transition-discontinuity gap, dead-reckoning bridge approaches [43,44] rely on speed-dependent filter parameters that cannot yet adapt dynamically to abrupt mobility-mode shifts or non-linear topologies such as multi-floor buildings; research is needed on adaptive handover models that jointly infer mobility state and transition topology to reconfigure fusion parameters in real time. For the computational-burden gap, federated learning [47] reduces centralized training dependency but leaves inference-phase burden on edge devices unresolved, motivating split-inference architectures in which lightweight on-device modules handle real-time preprocessing while intensive feature extraction is offloaded to edge servers.

4.2. Navigation Data-Related Technical Gap Analysis and Future Research Directions

The data present two fundamental gaps. First, outdoor 2D node–link networks [52–54] and indoor 3D mesh/grid/floor structures [65–67] differ structurally, and existing integration relying on simple coordinate matching [29,73,74] fails to guarantee topological connectivity at entrances, forcing navigation systems to halt and reload maps at indoor–outdoor transitions. Second, semantic information compatibility across mobile entities is insufficient: spatial data models are optimized for specific agents, primarily humans [77–80] or robots and autonomous vehicles [81–83], so attributes one agent requires (e.g., door operability, curb height) are routinely absent from data structured for another, blocking integrated cross-agent services.

Resolving these inconsistencies requires a hierarchical graph integration model. While standards such as IndoorGML [67] and CityGML [70] provide domain-specific hierarchies, and prior work establishes anchor-node connections between outdoor and indoor networks [29,73,74], these treat transition points as simple geometric endpoints rather than semantically rich nodes. A three-layer architecture is proposed instead: a macroscopic topological layer representing transition zones (entrances, elevators, transit interchanges) as attributed nodes encoding traversability and real-time congestion; a microscopic geometric layer retaining each domain’s native format for precision path computation; and a semantic attribute layer mapping agent-specific properties to spatial objects. This must be paired with dynamic semantic mapping technology updating the semantic layer in real time from IoT sensor streams; while building-scale digital twins have demonstrated

this for single-building robot navigation [71], propagating updates across a multi-building, multi-domain urban scale within navigation-relevant latency remains a core open challenge.

4.3. Route Planning-Related Technical Gap Analysis and Future Research Directions

Existing route-finding algorithms oversimplify transition processes in two ways. First, uncertainty in transition spaces (transfer zones, elevator waiting areas, security gates) is largely treated as fixed cost or simple distance [3,6,99], failing to reflect actual waiting times and congestion and degrading arrival accuracy. Second, multimodal route planning focuses on minimizing the simple sum of per-mode shortest costs [100–102], without accounting for mode-change frequency, payment interoperability, or weather-dependent route preferences that genuinely seamless navigation requires.

Addressing this requires probabilistic cost modeling for transition-space uncertainty. Time-dependent routing approaches such as CSA and RAPTOR [30,92] and real-time congestion inputs [104,105] capture deterministic variability and current-state estimates, respectively, but neither models the stochastic nature of transition-space dwell times. Empirical dwell-time distributions per transition type (elevator waits, security queuing, intermodal transfer delay) should be integrated as stochastic cost terms into existing schedule-based algorithms [30,92] to enable probability-weighted arrival estimation. Beyond this, context-based routing reflecting user preferences (e.g., minimizing transfer resistance, prioritizing underground routes in rain) is needed; ref. [102]’s action-point framework offers a partial foundation, extendable toward a multi-dimensional utility function inferring context weights from user behavior history for personalized route computation.

4.4. Route Guidance-Related Technical Gap Analysis and Future Research Directions

Guidance-system context resetting causes the most direct inconvenience when users change transport modes or move through spaces: failure to automatically transfer mobility context (destination, route, progress) between systems forces re-entry of destinations or app switching, and related research on cross-platform session continuity remains insufficient [31,32]. Additionally, in shared human–robot spaces, current guidance systems provide only individual information without considering inter-agent interaction, for example, cooperative guidance for recognizing and yielding to another’s movement intent in a narrow corridor is absent [124,125].

Addressing these gaps requires a cross-platform session-persistence protocol that serializes the full mobility-context state (destination, route progress, modal-transition history, device registry) into a lightweight handover object transferable across platforms [32], triggering serialization at detected transition events and restoring state on the receiving device within real-time latency bounds. For human–robot shared spaces, intent-predictive guidance architectures are needed in which each agent maintains a probabilistic trajectory model of co-present entities, drawing on shared semantic maps [125] and reinforcement-learned path planners [126], to adaptively issue behavioral instructions based on predicted conflict probability, complemented by LLM-based dialogue managers [122] that deliver proactive re-routing and clarification across modal handovers through natural language.

4.5. Integrated Gap Analysis and Integrated Research Directions

Based on the four core technology components discussed so far, Table 4 comprehensively summarizes the technical requirements for seamless navigation implementation, the major gaps identified in this study, and future research directions to overcome them.

Table 4. Summary of requirements, gaps, and research directions by core technology component for seamless navigation.

Core Component	Technical Requirements	Identified Major Gaps	Future Research Directions
Positioning	Continuous position estimation regardless of indoor/outdoor environment	Signal discontinuity and handover delay at transition zones (outdoor <> indoor)	Multi-sensor fusion positioning with proactive environmental change recognition
	Error range minimization and high reliability	Positioning models optimized for single environments	Dynamically adaptive continuous positioning models
Navigation Data	Standardized interoperable data models	Topological and structural inconsistency between outdoor (network) and indoor (grid/mesh)	Hierarchical graph integration model spanning indoor–outdoor
	Real-time information reflection and inter-object compatibility	Lack of semantic compatibility between agents (human, robot)	Semantic maps with dynamic attributes
Route Planning	Optimal route computation considering multiple modes	Static treatment of transition-space uncertainty (transfer, entry)	Probabilistic cost modeling for transition spaces
	Minimization of travel time and transition costs	Limited multimodal optimization confined to single modes	Pareto-optimal routing with empirical transition-cost distributions
Route Guidance	Customized information provision based on user context awareness	Mobility context disconnection and reset upon mode/space transitions	Cross-platform session persistence protocol for mobility context handover
	Consistent guidance maintained across mode changes	Absence of cross-platform information transfer	Intent-predictive guidance for human–robot shared spaces
		Lack of inter-agent guidance coordination in shared human–robot spaces	LLM-based dialogue management for modal handovers

This section analyzed the limitations that must be overcome for seamless navigation and derived future research directions for each core component. While positioning, navigation data, route planning, and route guidance technologies have each reached high maturity within single domains, they remain disconnected at domain boundaries. Seamless navigation therefore requires an integrated architecture in which (1) uninterrupted positioning transition, (2) semantic data interoperability, (3) transition-space-aware route planning, and (4) context-preserving cross-agent route guidance work organically together; the R&D paradigm must accordingly shift from fragmented component-level advancement toward whole-system connectivity and continuity. Section 5 draws synthesized conclusions from these implications and discusses the study’s limitations and future tasks, including non-technical factors.

5. Discussion and Conclusions

This study critically examined the current state of technology and the research directions that must be pursued for implementing ‘seamless navigation,’ which is essential for the advancement of smart cities and the proliferation of MaaS. A key finding confirmed through the literature analysis is that while individual navigation technologies have reached considerable maturity within their respective domains, a ‘technological silo’ phenomenon exists in the process of integrating them. Based on the analysis in Section 4, the implications of the paradigm shifts required across the four core technology components for building an uninterrupted mobility environment are as follows.

First, positioning technology requires a shift from ‘static accuracy’ to ‘dynamic adaptability.’ Existing isolated positioning models inevitably cause handover delays and positional errors at indoor–outdoor transition zones. Future positioning systems must evolve beyond simple coordinate computation into continuous, flexible systems that proactively recognize and adapt to changes in the user’s surrounding environment through multi-sensor fusion.

Second, data integration must go beyond physical alignment to secure ‘semantic interoperability.’ Simple coordinate system matching of indoor–outdoor maps does not guarantee true seamlessness. Hierarchical integration models and standardization of attribute information must become the top priority, enabling diverse mobility agents (humans, autonomous vehicles, robots) to understand and share the state of the same space in real time.

Third, route planning must advance from ‘single-mode optimization’ to ‘probabilistic control of transition spaces.’ The key factor determining overall travel efficiency and user experience is the uncertainty arising during transition processes such as transfers and space entries. Therefore, rather than simple multi-modal combination, user-centered optimization algorithms that probabilistically model transition costs and maximize seamless utility are needed.

Fourth, route guidance must evolve from a device-centric to a user mobility context-centric approach. The phenomenon of guidance resetting when transport modes or spaces change represents a critical service disruption. Concretely, a cross-platform session persistence protocol that serializes and transfers the complete mobility context state across heterogeneous devices, intent-predictive guidance architectures that coordinate behavioral instructions for co-present humans and robots in shared spaces, and LLM-based dialogue managers that preserve navigational continuity through natural language interaction across modal handovers are required.

Across the four component analyses conducted in this study, we argue that the identified gaps are not independent phenomena but rather symptoms of a single structural deficit: the absence of an integrated system design that treats heterogeneous navigation components as a unified architecture. Translating this conceptual position into a concrete system design; specifying the interfaces among positioning, navigation data, route planning, and route guidance, the semantic data layers that mediate their exchange, transition-space cost models, and session handover mechanisms; constitutes a dedicated architecture-design effort beyond the scope of this critical review and is identified here as a priority direction for future work. While each component gap merits dedicated research attention, we contend that semantic data interoperability; the capacity for diverse mobility agents to interpret and share spatial state representations through a common hierarchical model; constitutes the most fundamental prerequisite for seamless navigation. Without this shared semantic substrate, advances in positioning accuracy and route optimization remain locally contained improvements that cannot propagate across system boundaries to yield genuine seamlessness. In terms of near-term research strategy, we further assess that LLM-based

dialogue management for modal handovers represents the most immediately deployable pathway to user-perceived seamlessness: unlike positioning infrastructure or semantic data standardization, which require long-horizon coordination across hardware, standards bodies, and industry stakeholders; LLM-based systems operate at the application layer and can bridge guidance discontinuities through contextual inference without awaiting full resolution of the underlying technical gaps. We therefore propose a dual-track research agenda: prioritizing semantic interoperability standards as the long-term infrastructure foundation, while concurrently advancing LLM-based guidance coordination as a near-term bridge that delivers service continuity in advance of complete technical integration.

In conclusion, the realization of truly seamless navigation can never be achieved through fragmented performance improvements of individual component technologies. It can only become feasible when a ‘redesign of the integrated system architecture’ is undertaken first, where all stages (positioning, navigation data, route planning, and guidance) mesh organically together. For the mobility services that serve as the circulatory system of smart cities to create genuine value, eliminating the logical ‘disconnections’ arising from the lack of connectivity between heterogeneous systems and the absence of integrative thinking is paramount, beyond merely expanding hardware infrastructure. The integrated technology architecture derived from core components examined in this paper represents an R&D milestone necessary for the future realization of complete door-to-door services. Only when these technological gaps are organically bridged can the truly hyper-connected smart city be completed, one where the boundaries between indoor and outdoor, heterogeneous mobility modes, and even virtual and physical reality are dissolved.

Meanwhile, this study critically defined and analyzed the core component technologies for seamless navigation implementation from an integrated systems perspective and presented directions for technological advancement. However, it has limitations in that consideration of non-technical factors due to the delineation of research scope is somewhat insufficient. For the full commercialization of seamless navigation, not only must the technical gaps presented in this study be resolved, but privacy protection and location information security issues arising from the data fusion process among diverse mobility stakeholders (e.g., platforms, manufacturers, infrastructure operators) must be addressed as prerequisites. Furthermore, legal and institutional standardization must proceed in parallel to clearly define the liability in case of accidents during inter-system handover and transfer of autonomous mobile entity control authority. Even if the proposed architecture achieves high technical completeness, serious constraints on actual service deployment will inevitably follow if such social consensus and institutional mechanisms are absent. Additionally, while specific operational indicators for assessing seamlessness are proposed in Section 2.5, the precise threshold values for each metric are context-dependent and require empirical calibration across diverse deployment environments, which remains as a direction for future research. More broadly, the four indicators are intended as future evaluation criteria for assessing seamlessness across candidate architectures, rather than as instruments applied retrospectively to the studies reviewed in this critical review. Therefore, in subsequent research, we intend to contribute to the practical diffusion of seamless mobility services by conducting an in-depth examination of policy and institutional linkage strategies encompassing information protection framework construction and legal liability allocation among stakeholders within the actual industrial ecosystem, building upon the integrated technology architecture derived in this paper.

Furthermore, the analytical framework established in this study, comprising the four core navigation components and their associated seamless integration requirements, can serve as a structured foundation for future systematic reviews targeting individual components. As the body of literature in this domain continues to grow, component-specific

systematic reviews adopting protocols such as PRISMA would enable more reproducible and quantitatively rigorous mapping of the research landscape, complementing the integrative perspective offered by the present critical review.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/ijgi15070290/s1>, Table S1. Complete List of Reviewed Papers. Table S2. Positioning Rationale for Each Reviewed Literature Cluster Along X-Axis and Y-Axis.

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Abbreviations

The following abbreviations are used in this manuscript:

MaaS	Mobility as a Service
ISO	International Standard Organization
OGC	Open Geospatial Consortium
GNSS	Global Navigation Satellite System
UAM	Urban Air Mobility
UWB	Ultra-Wideband
VPS	Visual Positioning Systems
SLAM	Simultaneous Localization and Mapping
SNR	Signal-to-Noise Ratio
DR	Dead Reckoning
PDR	Pedestrian Dead Reckoning
POI	Points of Interest
GDF	Geographical Data Format
NDS	Navigation Data Standard
CH	Contraction Hierarchies
CSA	Connection Scan Algorithm
RAPTOR	Round-Based Public Transit Optimized Router
RRT*	Rapidly-Exploring Random Tree Star
AR	Augmented Reality
HUD	Head-Up Display
C-ITS	Cooperative-Intelligent Transportation System

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