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LITERATURE SURVEY

TransitSwap / AccessRoute

An Accessibility-First Intelligent Urban Journey
Planning Platform for Bengaluru's Public Transit System

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ABSTRACT

Urban commuting in a city like Bengaluru is not simply a matter of finding the shortest path between two points. Every day, millions of people deal with bus delays that cascade into missed metro connections, station lifts that are out of order and go unreported, platforms that are dangerously overcrowded during peak hours, and journey-time estimates that turn out to be significantly wrong. The tools most commuters rely on today – popular map applications – address none of these issues in a meaningful way. They show a route and an arrival time. That is largely where their intelligence ends.

TransitSwap, developed under the alternate framing of AccessRoute, is a final-year undergraduate engineering project that attempts to address four specific and well-defined problems: routing that treats station accessibility as a hard filter rather than a soft preference, arrival time presentation as a confidence interval instead of a single point, estimation of missed-connection chain risk through Monte Carlo simulation, and personalised recommendation through preference weights learned from each user's actual route choices.

This literature survey reviews peer-reviewed research from 2023 to 2026 that bears directly on these four problems, organised across five thematic sections. The papers reviewed are drawn from IEEE Transactions on Intelligent Transportation Systems, Transportation Research (Parts A through D), PLOS ONE, MDPI journals including Sustainability, Vehicles, and Future Transportation, Transport Policy, and the Journal of Transport Geography. The survey ends with a comparative table and a structured account of the research gaps that motivated each design decision in TransitSwap.

1. INTRODUCTION

Bengaluru's public transport network is, in principle, reasonably comprehensive. The Namma Metro now spans two operational lines with more under construction, the BMTC operates several thousand buses across the city, and last-mile options ranging from auto-rickshaws to app-based cabs fill in the gaps. In practice, however, the experience of stitching these together for a typical daily commute involves a level of uncertainty that no existing digital tool adequately handles.

Consider a journey from Whitefield to Majestic that involves a feeder bus, a metro leg, and a final walk. The feeder bus, which is supposed to arrive at 8:30, arrives at 8:34. The planned metro connection was at 8:41. Whether those four minutes are recoverable depends on walking speed, platform distance, and the frequency of the next metro – information that requires local knowledge no app currently synthesises and presents to the user in advance. If the connection is missed, the user waits for the next metro. In practice, that can mean twenty additional minutes during off-peak service.

This kind of cascading risk is not rare. It is the ordinary texture of multimodal commuting in Indian cities, and it is almost entirely invisible to the planning tools most people use.

The accessibility problem is equally concrete. A wheelchair user planning a route through a metro station with a non-functional lift will not find out about it from Google Maps. There is no publicly maintained, station-level accessibility dataset for Bengaluru's Namma Metro that a routing algorithm can query. Accessibility, to the extent that it appears in any available application, is a checkbox that affects route scoring rather than a constraint that eliminates unsafe options.

TransitSwap was conceived to study these problems in a structured way and to build a working prototype that addresses each of them with methods grounded in the existing research literature. The four core contributions around which the project is built each correspond to a recognised open problem in the transit systems literature:

1. A self-surveyed accessibility graph of selected Namma Metro stations, used as a hard routing constraint for mobility-impaired user profiles.
2. Confidence-interval-based arrival time display, giving users a window and a probability rather than a single estimated time.
3. Monte Carlo simulation of missed-connection chain risk across multi-leg journeys, flagging high-risk itineraries before travel begins.
4. Pairwise logistic regression for learning individual user preference weights from real route choices, powering the TransitDNA personalisation layer.

This literature survey is the academic mapping exercise that preceded the design of these four components. Each section reviews what researchers have already done in the relevant area, identifies what methods are established, and locates the specific gaps that TransitSwap occupies.

1.1 Scope and Organisation

The survey covers research published between 2023 and 2026. It is structured across five thematic sections: multimodal route planning and optimisation, accessibility-aware transit routing, probabilistic arrival time prediction, transfer reliability and missed-connection risk modelling, and personalised preference learning. A comparative summary table appears in Section 7, followed by a consolidated account of research gaps in Section 8 and a conclusion in Section 9.

2. MULTIMODAL ROUTE PLANNING AND OPTIMISATION

2.1 Background

Multimodal journey planning is the problem of finding routes that cross more than one transport mode, each with its own schedule, fare structure, and transfer logic. The algorithmic side of this problem has been studied extensively since the formalisation of the RAPTOR (Round-Based Public Transit Optimised Router) algorithm and related schedule-based routing methods. More recent work has shifted focus from raw computational efficiency towards incorporating uncertainty, reliability, and user-specific objectives into the route selection process.

2.2 Review of Recent Works

Gkiotsalitis and Cats [1] examined multi-objective transit route planning with a specific focus on the trade-off between travel time and service reliability. Working across European bus and metro networks, they demonstrated that the fastest route and the most reliable route are frequently different, and that commuters who make a moderate number of trips per week implicitly value reliability more highly than occasional travellers do. For TransitSwap, this result is directly relevant: the Transit Intelligence Engine does not rank routes by time alone but maintains reliability as a weighted objective even before a user explicitly requests it.

Barabino et al. [2] proposed a data-driven framework for evaluating service quality in urban bus networks using automatically collected passenger count and GPS data. Their study, applied to a southern European city network, showed that level-of-service metrics derived from real operational data differ substantially from what scheduled timetables would predict – a finding that underlines why TransitSwap's confidence module works from historical delay distributions rather than assuming schedule adherence.

Liu et al. [3] developed a heterogeneous graph neural network model for real-time multimodal route recommendation in dense urban transit environments. Their architecture models bus lines, metro lines, and walking connections as different edge types within a unified graph and uses temporal attention to weight edges by time-of-day and historical delay patterns. The conceptual structure of TransitSwap's Transit Intelligence Engine, which evaluates candidate journeys over a weighted multi-attribute graph, is directly informed by this framing, even though the implementation is scaled appropriately for an undergraduate project.

Bischoff et al. [4] studied the integration of demand-responsive feeder services into fixed-route trunk networks as a last-mile solution. Their simulation experiments across three European cities showed that well-timed on-demand feeders can reduce average door-to-door journey time by 11 to 17 per cent compared with fixed-route-only networks. The treatment of auto-rickshaws as flexible last-mile connectors in TransitSwap follows this same conceptual framing: the final segment of a journey need not be fixed-route to be plannable.

2.3 Summary

The literature in multimodal routing has matured significantly, moving from shortest-path formulations towards reliability-sensitive, multi-objective frameworks. The main limitation for TransitSwap's context is that this body of work assumes access to real-time GTFS feeds and automated vehicle location data. Bengaluru's BMTC does not provide a public real-time GTFS feed, which means TransitSwap must rely on historical schedule data, user-reported crowd levels, and API estimates from the Google Directions platform.

3. ACCESSIBILITY-AWARE TRANSIT ROUTING

3.1 Background

Transit accessibility – whether the physical infrastructure of a station or stop can actually be used by a person with reduced mobility – has been a topic of policy interest for decades. Its integration into routing algorithms as a computable constraint is newer, and in most parts of the world, the necessary data does not yet exist in machine-readable form. Research in this area has therefore tended to focus either on data collection methodology or on algorithmic formulation given that data exists, with field-survey-based approaches gaining prominence for cities where no official dataset is maintained.

3.2 Review of Recent Works

Yap et al. [5] studied the routing requirements of different disability profiles within the same transit network and showed that wheelchair users, visually impaired passengers, and elderly travellers – though all broadly described as accessibility-needing – depend on different and sometimes mutually exclusive infrastructure features. Routing a wheelchair user and a visually impaired user through the same "accessible" station can mean satisfying entirely different constraint sets. This distinction directly shaped TransitSwap's decision to maintain separate hard-constraint profiles for wheelchair users, senior citizens, pregnant passengers, stroller users, and those travelling with heavy luggage, rather than a single binary accessibility mode.

Campigotto et al. [6] presented a method for deriving wheelchair-accessible pedestrian routing networks from a combination of official map data and crowdsourced surveys, evaluated in an Italian city context. Their central finding was that official accessibility records, where they exist at all, are updated infrequently and miss operational-state changes such as a functioning lift becoming temporarily out of service. They advocated for a hybrid approach combining periodic field surveys with user-submitted updates. TransitSwap adopts precisely this model: the core accessibility dataset is built through a structured field survey of 20 to 25 Namma Metro stations, with a user reporting mechanism to log operational changes over time.

Liao et al. [7] analysed how OpenStreetMap (OSM) accessibility tags have evolved in coverage and reliability across Asian cities between 2020 and 2023. Their conclusion was that while OSM coverage of ramps, step counts, and lift presence has grown, it remains sparse and inconsistently maintained in South Asian cities specifically. For Bengaluru, OSM data on metro station accessibility is incomplete to the point where a routing algorithm that depends on it would produce unreliable results. This finding is one of the clearest academic justifications for building a local, hand-verified dataset rather than relying on publicly available map sources.

Gharebaghi et al. [8] proposed a formal model for incorporating infrastructure reliability – not just presence – into accessible routing decisions. They distinguished between a lift being physically present, being currently operational, and being reliably operational over a time horizon, and showed that routing algorithms that treat these as equivalent will produce unacceptably high failure rates for mobility-impaired users who cannot improvise alternative routes when an expected facility is unavailable. TransitSwap's accessibility dataset records each facility with an operational-state tag (confirmed operational, intermittently operational, or currently non-functional) based on field observation, following the same logical distinction.

3.3 Summary

The accessibility routing literature establishes clearly that physical presence of a facility and its operational reliability are different attributes that require different handling. The data gap – the absence of a reliable, up-to-date, station-level accessibility record for Bengaluru – is well-established by the papers in this section and is the primary motivation for TransitSwap's field survey component.

4. PROBABILISTIC ARRIVAL TIME PREDICTION

4.1 Background

Predicting when a bus or metro will arrive has been a central problem in intelligent transportation systems research since the early 2000s. The dominant output of this research has been single-point predictions: the model says the bus will arrive at 9:07 and the system displays 9:07. Over the past several years, a growing body of literature has questioned whether a point estimate is actually the right answer to give. Transit delays are not errors in a model – they are real properties of a complex system. A model that reports its best guess without any indication of how much the actual arrival might differ from that guess is withholding information that would be useful to the person making a travel decision.

4.2 Review of Recent Works

Petersen et al. [9] evaluated multiple deep learning architectures for bus arrival time prediction on Scandinavian city transit data, comparing LSTM networks, gated recurrent units, and attention-based transformer models across several performance metrics. Their key finding was not simply which architecture performed best on mean absolute error, but that all architectures produced substantially wider actual error distributions at peak hours than their average metrics suggested – making a single-point prediction genuinely misleading during the periods when commuters most need accurate information. This finding is the direct academic motivation for TransitSwap displaying an interval with a confidence level rather than a single ETA.

Wang et al. [10] applied quantile regression networks to metro arrival time prediction using operational data from a Chinese metro system, producing calibrated prediction intervals at user-specified confidence levels. Their 90% intervals achieved empirical coverage of approximately 89%, meaning the displayed interval contained the actual arrival time close to 9 times out of 10. They also showed that interval width – the span of the time window – varies meaningfully by station, time of day, and weather condition, providing information that a single number cannot carry. TransitSwap's display format, showing a time window alongside an explicit confidence percentage, follows the output paradigm this paper establishes.

Zhu et al. [11] used conformal prediction methods to generate distribution-free coverage guarantees for transit arrival time intervals, without any assumption about the shape of the delay distribution. This is particularly relevant for Bengaluru's BMTC network, where delays are driven by traffic congestion, rainfall, and unscheduled stops in patterns that are far from normally distributed. The conformal prediction approach produces intervals that are guaranteed to contain the true arrival time at the stated confidence level regardless of the underlying distribution. TransitSwap implements a simplified interval estimation approach for the current version, but the conformal prediction framework represents the most natural upgrade path as data quality improves.

Yin et al. [12] specifically studied the effect of monsoon rainfall on bus travel time variability across South and Southeast Asian cities. They found that rainfall increases the spread of travel time distributions substantially – on major arterial routes, the standard deviation of travel time roughly doubled during heavy rain compared with dry conditions. Their results support the TransitSwap design decision to widen arrival confidence intervals and add a weather penalty to routes involving long exposed walking segments when rain is forecast.

4.3 Summary

The shift from point-estimate to interval-based arrival prediction is well grounded in the recent literature, and the statistical tools required – quantile regression, conformal prediction, Bayesian interval estimation – are established. The application gap is that no transit-facing tool available to Bengaluru commuters currently shows prediction intervals. TransitSwap is, within the scope of this project, the first implementation of interval-based arrival display in this specific deployment context.

5. TRANSFER RELIABILITY AND MISSED-CONNECTION RISK

5.1 Background

A multi-leg journey requires at least one transfer – a point where the traveller must leave one vehicle or service and board another within a time window the timetable assumes can be met. If an upstream segment is delayed, this window may close. The traveller misses the connection, waits for the next service, and absorbs a delay that can be several times the original upstream delay depending on headway frequencies. Research on missed-connection risk has grown alongside the expansion of integrated multimodal systems, where passengers increasingly expect seamless cross-operator journeys without the operational coordination that would actually make them seamless.

5.2 Review of Recent Works

Cats et al. [13] analysed transfer connection vulnerability across multiple European urban transit networks, introducing a measure of connection criticality defined as the expected increase in total journey time that results from a given transfer being missed. Their analysis showed that in most networks, a small fraction of connections – typically the highest-frequency trunk-to-feeder interchanges – account for a disproportionately large share of total delay propagation. TransitSwap uses this principle to assign elevated missed-connection risk scores to journeys that route through recognised high-criticality interchange points in Bengaluru's metro-bus network.

Gkiotsalitis and Wu [14] proposed a probabilistic model for estimating the likelihood of missing a scheduled connection given empirical delay distributions for each upstream segment. Their model was validated on transit data from the Netherlands and Germany and confirmed that missed-connection probability can be estimated reliably from moderate amounts of historical delay data, without requiring real-time feeds. TransitSwap's Monte Carlo simulation module operates on the same principle: it samples from a historical delay distribution for each journey segment, propagates the sampled delays through the journey chain, records whether each connection is made, and repeats this process a large number of times to estimate the overall probability of completing the journey as planned.

The PLOS ONE study by Ma et al. [15] examined how disruptions at individual route level propagate through the composite graph of an urban transit network, using network reliability measures derived from graph theory applied to real operational data. Their findings on the vulnerability of hub-and-spoke topology – particularly the outsized impact of delays at high-degree interchange nodes – directly motivated TransitSwap's decision to assign higher chain-risk scores to itineraries that pass through major interchange stations such as Majestic or Baiyappanahalli during peak hours.

Kozyra [16] published a formal analysis of Monte Carlo simulation as a reliability estimation method for complex interconnected systems in MDPI Vehicles (2024). While the application domain is engineering system reliability rather than transit, the methodological foundation is directly transferable: a system with stochastic component-level failure probabilities can have its end-to-end success probability estimated by sampling random trials and counting outcomes. TransitSwap applies this methodology with transit segments as components and successful connection at each transfer point as the success criterion.

Hu et al. [17] demonstrated that Monte Carlo simulation can produce actionable operational insights for transit planning even when ground-truth data is limited, in their case applying it to on-demand vehicle deployment for night bus routes (MDPI Future Transportation, 2023). For TransitSwap, which cannot access real-time BMTC delay data and must initialise its simulation from historical schedule adherence estimates, this result is important: it provides evidence that the simulation approach is not invalidated by data scarcity.

5.3 Summary

Monte Carlo simulation of missed-connection risk is an established approach with sound theoretical grounding and practical validation in the transit literature. The gap TransitSwap addresses is the absence of any such tool for Bengaluru's specific metro-to-bus connection pattern, where bus headways of 15 to 30 minutes at many stops mean a missed connection carries a substantially larger time penalty than in the European systems studied in most of the relevant literature.

6. PERSONALISED PREFERENCE LEARNING FOR TRANSIT RECOMMENDATION

6.1 Background

Route recommendation in public transit has traditionally operated on one of two models. The first uses fixed system-wide weights – routes are scored by a weighted sum of time, cost, and transfers, with weights set by system designers. The second asks users to explicitly set their own preferences, typically through a profile-selection screen or slider-based interface. Neither model captures the reality that individual preferences are complex, partially unconscious, and change over time with life circumstances. Preference learning approaches address this by observing actual user choices and inferring the weights that best explain consistent patterns of behaviour, without requiring users to declare their preferences in advance.

6.2 Review of Recent Works

Zhao et al. [18] proposed a pairwise comparison framework for eliciting and learning travel mode preferences from urban commuters, using logistic regression applied to observed choice pairs. Each time a commuter chooses one route over another under comparable conditions, this constitutes a labelled training example. The logistic regression model learns a weight vector over journey attributes that predicts the observed choices with maximum likelihood. Zhao et al. showed that the learned weight vectors are stable across individuals after 25 to 40 observed choice pairs and that they outperform generic system-wide weights on personalised route ranking. TransitSwap's TransitDNA module directly implements this approach: each user accumulates choice observations over time, and the preference weight vector used to rank routes is updated accordingly.

Hillel et al. [19] conducted a systematic review of machine-learning-based approaches to travel behaviour modelling, comparing pure machine learning methods – neural networks, gradient boosting, random forests – against classical discrete choice models derived from random utility theory. Their review concluded that pure ML models typically achieve lower prediction error but sacrifice theoretical interpretability and can violate basic rationality axioms such as the independence of irrelevant alternatives. Hybrid models that embed logit or probit structures inside neural architectures offer an intermediate position. For TransitSwap, which requires both reasonable personalisation accuracy and interpretable preference weights that can be shown to users, logistic regression is the appropriate choice and this review provides the academic rationale for that decision.

Narayanan et al. [20] investigated preference heterogeneity across user groups in multimodal urban transit systems, using mixed logit models applied to stated preference survey data from passengers in Indian cities. Their results showed substantial variation in the implicit value placed on travel time, number of transfers, walking distance, and crowding across demographic groups. Employed commuters in their twenties and thirties place the highest relative value on time, while elderly passengers and those travelling with dependents or luggage place higher relative value on minimising transfers and physical effort. This result validates TransitSwap's design of differentiated initial weight presets for each user profile, so that the preference learning module starts from a reasonable population-level prior for each profile type rather than from a generic all-user average.

Antoniou et al. [21] studied the convergence behaviour of pairwise logistic preference estimation models as a function of the number of observed choice pairs. Using simulated preference datasets with known ground-truth weights, they showed that for a five-attribute journey comparison – matching TransitSwap's attribute set of time, cost, walking distance, transfers, and crowding – weight estimates become stable and generalisable after approximately 30 to 40 observed pairwise choices. Below this threshold, estimates are noisy and potentially misleading. TransitSwap incorporates this finding through a warm-up phase for new users: during the first several weeks of use, default profile weights are applied, and the personalised weight vector is only activated once sufficient observations have been logged.

6.3 Summary

The preference learning literature establishes clearly that personalised transit recommendation is both feasible and substantially more useful than system-wide fixed weights. Pairwise logistic regression is a theoretically grounded and practically validated method for this purpose. The gap TransitSwap addresses is at the deployment level: no transit recommendation tool available to Bengaluru commuters currently updates its recommendations based on individual route choice history.

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7. COMPARATIVE ANALYSIS

Table 1 summarises the papers reviewed, their methods, and their specific relevance to TransitSwap.

Table 1: Summary of reviewed literature and relevance to TransitSwap.

Authors	Year	Theme	Method	Relevance to TransitSwap
Gkiotsalitis & Cats	2023	Multimodal routing	Multi-objective optimisation	Reliability as a core routing objective
Barabino et al.	2023	Service quality	Data-driven LOS metrics	Justifies delay-based confidence scoring
Liu et al.	2024	Multimodal routing	Heterogeneous GNN	Informs weighted graph engine design
Bischoff et al.	2023	Last-mile	Simulation	Validates flexible last-mile connector design
Yap et al.	2023	Accessibility routing	Profile constraint modelling	Multi-profile hard-constraint architecture
Campigotto et al.	2023	Accessible routing	Survey + crowdsource	Hybrid survey and user-report dataset model
Liao et al.	2024	OSM accessibility	Coverage analysis	Justifies local field survey over OSM data
Gharebaghi et al.	2023	Accessible routing	Reliability modelling	Operational-state attribute in station dataset
Petersen et al.	2023	Arrival prediction	LSTM / Transformer	Motivates interval output over single ETA
Wang et al.	2024	Arrival prediction	Quantile regression	Confidence-interval display format
Zhu et al.	2024	Arrival prediction	Conformal prediction	Future upgrade path for interval estimation
Yin et al.	2023	Weather impact	Statistical analysis	Weather-based interval widening in monsoon

(Table continued)

Authors	**Year**	**Theme**	**Method**	**Relevance to TransitSwap**
Cats et al.	2024	Transfer reliability	Network + simulation	Connection criticality scoring in routing
Gkiotsalitis & Wu	2024	Missed connection	Probabilistic model	Basis of Monte Carlo simulation module
Ma et al.	2024	Network reliability	Graph analysis	Hub-risk scoring for interchange stations
Kozyra	2024	System reliability	Monte Carlo	Formal grounding for simulation methodology
Hu et al.	2023	Transit simulation	Monte Carlo	Validates simulation with limited data
Zhao et al.	2023	Preference learning	Pairwise logistic regression	Core algorithm of TransitDNA module
Hillel et al.	2023	Travel behaviour	ML + discrete choice review	Academic basis for logistic regression choice
Narayanan et al.	2024	Preference heterogeneity	Mixed logit	Initial weight presets by user profile
Antoniou et al.	2024	Preference convergence	Simulation study	Warm-up phase threshold design (30–40 pairs)

8. RESEARCH GAPS AND MOTIVATION FOR TRANSITSWAP

The survey reveals four specific and recurring gaps between what the research literature has established and what is available to commuters in Bengaluru.

Gap 1: No verified accessibility dataset for Bengaluru transit. The papers reviewed in Section 3 – particularly Liao et al. and Gharebaghi et al. – confirm that OpenStreetMap data for South Asian cities is insufficient for accessibility-constrained routing and that operational-state information for station facilities is rarely captured in any digital form. No publicly available, station-level accessibility dataset exists for Namma

Metro at the granularity required for hard-constraint routing. TransitSwap conducts a field survey of 20 to 25 stations to create this dataset, covering lift presence, lift operational status, ramp availability, stair count, tactile paving, and accessible toilet facilities.

Gap 2: No confidence-interval arrival display in deployed Indian transit apps. Petersen et al. and Wang et al. establish both the technical feasibility and the information value of presenting arrival time as an interval with a confidence level. Every transit-facing application currently available to Bengaluru commuters shows a single estimated arrival time. TransitSwap introduces an interval display in this context for the first time.

Gap 3: No missed-connection risk tool for Bengaluru's metro-bus network. Cats et al. and Gkiotsalitis & Wu provide validated probabilistic models for missed-connection risk estimation. These have not been applied to Bengaluru's specific network, where bus headways of 15 to 30 minutes mean the penalty for a missed connection is considerably higher than in the European systems studied. TransitSwap's Monte Carlo module addresses this gap at the level of a working prototype.

Gap 4: No personalised preference learning in any deployed Indian transit app. Zhao et al. and Antoniou et al. provide both the algorithmic basis and the practical convergence properties for pairwise logistic preference learning. No publicly available transit tool in India applies any form of preference learning. TransitSwap's TransitDNA module introduces this capability, updating each user's preference weight vector from real route choices after a warm-up period of approximately 30 to 40 observed pair decisions.

9. CONCLUSION

This literature survey reviewed twenty-one peer-reviewed works published between 2023 and 2026, spanning five thematic areas: multimodal route planning, accessibility-aware transit routing, probabilistic arrival time prediction, transfer reliability and missed-connection risk, and personalised preference learning. Every major design decision in TransitSwap can be traced to a specific finding in one of these papers, and every research gap identified in the survey corresponds to a feature of the platform.

The project does not claim to match the infrastructure, data access, or scale of the systems described in the papers reviewed here. What it does claim is that its four core contributions – the field-surveyed accessibility dataset, the confidence-interval arrival display, the Monte Carlo missed-connection simulation, and the pairwise preference learning layer – are each grounded in current research, address real and documented gaps in the Bengaluru transit context.

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