A Comprehensive Review on Type-2 Fuzzy Logic in Intelligent Transportation Systems

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ABSTRACT
This paper presents a comprehensive survey of the development, methodologies, and applications of Type-2 Fuzzy Logic System (T2FLS) in Intelligent Transportation Systems (ITS) over the period 2012–2025. Rapid improvements in autonomous vehicles, electric mobility, sensor-driven traffic control, and large-scale transportation optimization have increased real-time decision uncertainty. T2FLS models ambiguity based on noisy data, human behavior, environmental volatility, and dynamic system interactions within a principled framework. Drawing on over 50 key studies, this paper demonstrates that T2FLS outperforms Type-1 Fuzzy Logic System (T1FLS) approaches and classical control techniques in traffic signal control, autonomous navigation, anti-lock braking, electric vehicle energy management, driver behavior modeling, and evacuation routing by synthesizing more than 50 key studies. The review also examines methodological trends, constraints, and future research needs, providing a path for next-generation ITS integration of hybrid T2FLS.

General Terms
Artificial Intelligence, Type-2 Fuzzy Logic System, Intelligent Transportation Systems, Traffic Control, Autonomous Vehicles, Energy Management, Multi-Criteria Decision-Making, Optimization, Adaptive Control.

Keywords
Type-2 fuzzy logic, Interval Type-2 fuzzy sets, Intelligent transportation system, Uncertainty handling, Adaptive control, Sustainable mobility.

1. INTRODUCTION
ITS are under greater demands than ever because cities are changing quickly and transportation networks are getting more complicated. ITS must address contemporary urban mobility issues such as traffic congestion, road safety, energy efficiency, and the integration of sustainable infrastructure. As cities throughout the world grow faster by 2050, 68% of the world's population will live in cities [1]. ITS must address issues that are becoming more challenging and less certain. ITS has changed a lot in the past ten years because there are more electric vehicles (EVs), self-driving technologies, and real-time data from connected vehicles and infrastructure. These systems have to address built-in uncertainties, such as changing traffic patterns, human behaviors, sensor errors, and environmental factors. Traditional approaches to transport-related control and decision-making [2] have difficulties in dealing with uncertainty and imprecision in data; thus, traditional methodologies based on crisp logic and simplified models may fail to cope with real-world problems in many situations. To solve this problem, we use fuzzy logic, which deals with uncertainty due to its use of membership functions that accurately describe it [3]. T2FLS has emerged as a promising approach for ITS as compared to other fuzzy methods because it successfully deals with uncertainty and, therefore, offers additional flexibility through the inclusion of an uncertainty factor into the systems [4]. Type-2 fuzzy logic was first proposed by Zadeh in 1975 [5] and extended the existing fuzzy sets by allowing membership grades to be represented by fuzzy numbers, specifically by fuzzy intervals between 0 and 1. It tackles the problem of uncertainty in both the parameters of membership functions and the data itself. Type-2 fuzzy sets are used in situations where a precise definition of membership is impossible due to ambiguity in the system parameters. To achieve higher precision than what would be achieved with finite-type fuzzy sets, the membership function can be further fuzzification captures higher-order uncertainty, not absolute precision. It is also noted that, regardless of how many times a membership function [6] is fuzzification, there will always exist some level of uncertainty that will never be captured by a finite-type fuzzy set, as illustrated by the Footprint of Uncertainty (FOU). Interval type-2 fuzzy sets and generic type-2 fuzzy sets represent the two categories of type-2 fuzzy sets. Interval type-2 fuzzy sets have constant secondary memberships that are always equal to one. They are easy to compute, but they can't model things accurately or with higher precision. Generic type-2 fuzzy sets, on the other hand, have variable secondary memberships that can be any number between 0 and 1. They are harder to compute, but IT2FLS provide a practical balance between modeling uncertainty and computational feasibility [7].

T2FL is better than T1FL in terms of overall effectiveness, especially while controlling and making decisions in noisy environments. Its nature-inspired optimization techniques, such as genetic algorithms for parameter adjustment, can enhance benefits. T2FLS rises significantly in pattern recognition, control systems, and monitoring in its deployment in ITS since the early 2000s. IT also has applications in traffic control and management, improving signal prioritization and congestion reduction by its ability to adapt dynamically to inconsistent traffic patterns. In [8], the T2FLS traffic signal controller was enhanced by employing the Non-Dominated Sorting Genetic Algorithm (NSGA-II), which led to reduced delays and a shorter queue. lengths at related intersections by taking into account surrounding traffic volumes. According to [9], new developments combine T2FLS with AI to govern a single crossing. Their work is done by adjusting green times and removing bottlenecks using real-time flow data. To improve flow efficiency, [10] used T2FLS for city traffic management, which handles varying vehicle densities and linguistic uncertainty. In surveys of fuzzy applications in transportation, T2FL stands out for its capacity to simulate imprecise inputs such as "high congestion" or "moderate delay," which improves system responsiveness overall as compared to T1FLS [11].

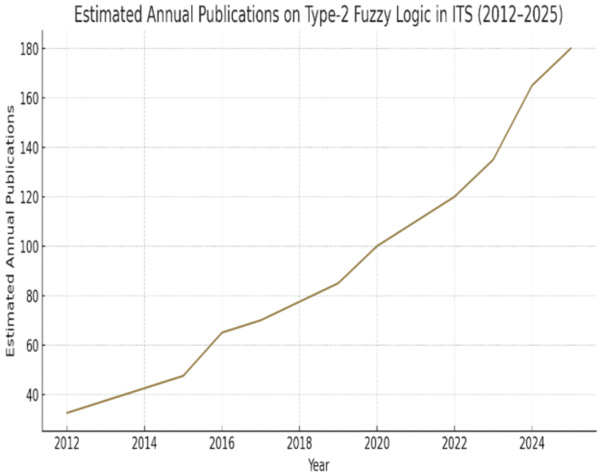

Figure 1. Estimated annual publication on T2FLS in ITS (2012-2025)

T2FL has solutions to the problems of steering and path planning and the communication between the human and automated systems in both self-driving and semi-driving cars. The IT2FLS method, proposed by [12], improves the lane keeping of semi-self-driving cars through the use of inaccurate premise variables. Obtained through sensor inaccuracies and driver conditions, therefore, ensuring strong stability as per the H-infinity and D-stability criteria. With mixed traffic navigation, [9] evaluated social value orientations on the basis of urges between vehicles and pedestrians and the use of T2FLS in combination with artificial potential fields. Furthermore, T2FLS with Proportional-Integral control, distance and navigation have been smoothed, and steering electric power speed inputs of the autonomous vehicle have been improved. Even the nonlinear dynamics of vehicles [13] are proven. Using evolutionary algorithms, researchers [14] and [15] developed mobile hierarchical T2FLS controllers. robots, which act as agents of autonomous cars, improving their obstacle avoidance capabilities and tracking flying over uncertain conditions. T2FLS is especially very skilful in sensor noise and behaviour management. Intelligent control applications vary [16]. Figure 1 demonstrates the fact that the number of publications has been increasing constantly between 2012 and 2025. This data shows that research interest is still increasing.

In another important area, Electric Vehicles (EVs), T2FL shows outstanding skill in managing energy. [17] made an adaptive T2FL controller for HEV (Hybrid Electric Vehicle) energy systems that switches between Type-1 and Interval Type-2 modes based on driving conditions like road slopes and traffic. The goal is to optimize torque distribution to improve fuel efficiency and lower pollution. [18] used a self-building T2FL neural network to change the speeds of electric vehicles based on how steep the road was. [19] also came up with an IT2 fuzzy neural network for EV anti-lock braking. This made it easier to manage slip ratios and recover energy when road adhesion changed. Furthermore, EV charging infrastructure planning is a notable application of T2FL within ITS. In [20], the authors proposed a T2FLS hybrid preference optimization approach for selecting charging station sites, which utilizes Gaussian T2 fuzzy variables to reconcile stakeholder interests with demand uncertainties. [21] demonstrated that IT2FLS outperformed genetic algorithms in achieving spatial allocation convergence for EV load distribution. Moreover, [22] explored hybrid AI-fuzzy Multi-Criteria Decision-Making (MCDM) frameworks for sustainable planning, integrating fuzzy Analytic Hierarchy Process (AHP) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) with machine learning for EV site selection and traffic resilience. These innovative solutions promote green travel and help prevent grid overloads.

2. FOUNDATION OF TYPE-2 FUZZY LOGIC

The design of type-2 FLS has mostly concentrated on the management of uncertainty in the information pertaining to the system. Presented evidence that a T2FLS performs better than a T1FL in a variety of ways; nonetheless, the design of the type-2 fuzzy rules is identical to that of the type-1 situations [23]. In T1FLS membership grades are unambiguous, limiting their ability to address ambiguities in some specified situation, such as noisy measurements or linguistic ambiguities. To solve this problem, extend T1FLS by incorporating a third dimension that represents uncertainty in the membership grades themselves. The Figure 2 illustrates the overall architecture of a Type-2 Fuzzy Inference System, beginning with crisp inputs that are transformed into Type-2 fuzzy sets through the fuzzifier and Footprint of Uncertainty (FOU).

A type-2 fuzzy set $\tilde{A}$ is defined as a bivariate function on the Cartesian Product $X \times [0,1]$, where X is the universe of discourse for the primary variable x, and the secondary variable $u \in [0,1]$ represents the primary membership degrees. Formally, it is expressed in point-valued representation as:

$$\tilde{A} = \{ ((x,u), \mu_{\tilde{A}}(x,u)) \mid \forall x \in X, \forall u \in J_x \subseteq [0,1], \mu_{\tilde{A}}(x,u) \in [0,1] \} \quad [1]$$

Where, J_x denotes the primary membership interval at x, $\tilde{\mu}_A(x,u)$ is the secondary membership function (SMF), also known as the secondary grade, satisfying $0 \leq \tilde{\mu}_A(x,u) \leq 1$.The SMF can also be denoted as $f_x(u)$.

The two-dimensional support of $\tilde{\mu}_A(x,u)$ forms the FOU:

$$FOU(\tilde{A}) = \{(x,u) \in X \times [0,1] \mid \mu_{\tilde{A}}(x,u) > 0\} = \cup_{x \in X} J_x \quad [2]$$

The FOU is bounded by the upper membership function (UMF) $\bar{\mu}_A(x)$ and the lower membership function (LMF) $\underline{\mu}_A(x)$:

$$\underline{\mu}_A(x) = inf\{u \mid u \in [0,1], \tilde{\mu}_A(x,u) > 0\}$$

$$\bar{\mu}_A(x) = sup\{u \mid u \in [0,1], \tilde{\mu}_A(x,u) > 0\} \quad [3]$$

Thus, $J_x = [\underline{\mu}_A(x), \bar{\mu}_A(x)]$. An alternative representation is: $\tilde{A} = \int_{x \in X} [\underline{\mu}_A(x), \bar{\mu}_A(x)] / x$

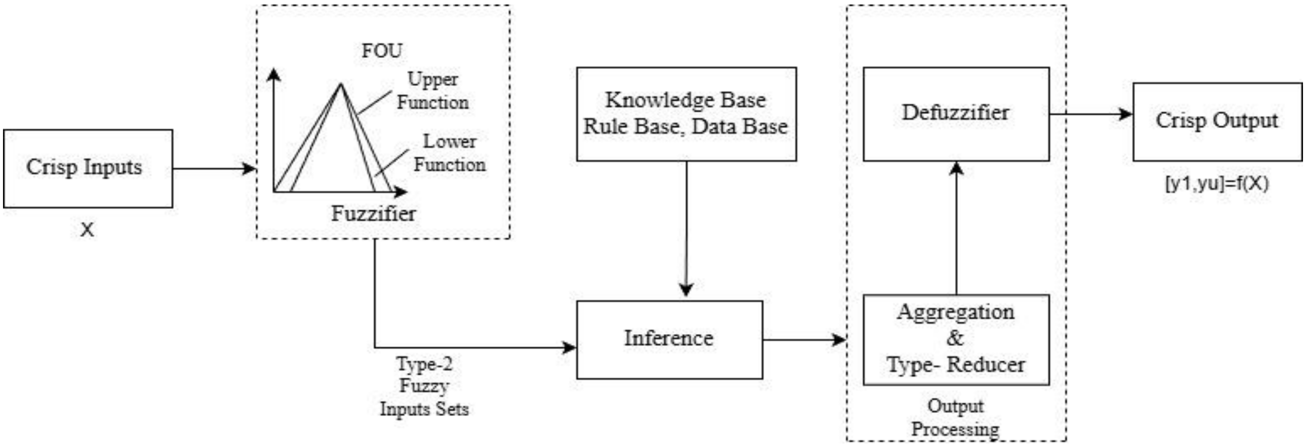

Figure 2. Architecture of a Type-2 Fuzzy Inference System

Blurring a type-1 membership function to the left and right introduces the third dimension, resulting in a general type-2 fuzzy set (GT2FS). Important embedded subsets are:

$$* \ Embedded\ type-2\ FS: \tilde{A}\_e = \int \{x \in X\}\ [f\_x(u(x))/u]/x, \quad u(x) \in J\_x$$

$$* \ Embedded\ type-1\ FS: A\_e = \int \{x \in X\}\ u/x, \quad u \in J\_x\ (serves\ as\ support\ of\ \tilde{A}\_e)$$

An interval type-2 fuzzy set (IT2FS) is the special case where all secondary grades equal 1:

$$\tilde{A} = \{ ((x,u),1) \mid \forall x \in X, \forall u \in J\_x \subseteq [0,1] \} = \int \_\{x \in X\}\ [\underline{\mu}\_\tilde{A}(x), \bar{\mu}\_\tilde{A}(x)] / x \quad [4]$$

A triangular IT2FS is parameterized by six values $(a_1, b_1, c_1, a_2, b_2, c_2)$:

$$\tilde{\mu}\_A(x) = t2trimf(x;\ a_1, b_1, c_1, a_2, b_2, c_2) \quad [5]$$

with LMF and UMF obtained as min(·) and max(·) of the two embedded triangles.

2.1 Type-2 Fuzzy Logic Systems

A type-2 fuzzy logic system T2FLS uses at least one type-2 fuzzy set to model uncertainty in antecedents and consequents.

- **Fuzzifier:** Maps crisp input $x = (x_1, \dots, x\_p)^\wedge T$ to an T2FLS $\tilde{A}\_X$. Singleton fuzzification is most common.
- **Rule Base:** M rules of the form: $R^\wedge l :\ IF\ x_1\ is\ F_1{}^\wedge l\ AND\ \dots\ AND\ x_p\ is\ F_p^\wedge l\ THEN\ y\ is\ G^\wedge l \quad (l = 1, \dots, M)$Firing interval using product t-norm - $F^\wedge l(x') = [f\_l\ , f\_l] = [\ \prod\{i = 1\}^\wedge p\ \underline{\mu}\{F\_i^\wedge l\}(x\_i')\ , \prod\{i = 1\}^\wedge p\ \bar{\mu}\{F\_i^\wedge l\}(x\_i')\ ]$
- **Inference Engine:** Produces rule output T2FLS $B^\wedge l(y|x')$ and aggregates them via maximum: $B(y|x') = \vee\_\{l = 1\}^\wedge M\ B^\wedge l(y|x')$
  Type-Reducer: Converts the output IT2FS into a type-1 interval (type-reduced set).
  Center-of-Sets (COS) type-reduction (most widely used):$Y\_COS(x') = [y\_l\ , y\_r] = [\ \sum\{i = 1\}^\wedge M\ f\_i^\wedge l\ y\_i^\wedge l\ /\ \sum\{i = 1\}^\wedge M\ f\_i^\wedge l\ , \sum\{i = 1\}^\wedge M\ f\_i^\wedge r\ y\_i^\wedge r\ /\ \sum\{i = 1\}^\wedge M\ f\_i^\wedge r\ ]$
  Switch points are found using the Enhanced Karnik–Mendel algorithm.
- **Defuzzifier:** Produces crisp output by averaging the endpoints: $y\_c(x') = (y\_l + y\_r)/2$

3. LITERATURE AND METHODOLOGICAL REVIEW

In this section, a comprehensive review of recent literature on T2FLS in ITS, we derived from a corpus of over more than 50 seminal works from the period of 2012-2025. Classifies the applications hierarchically across domains such as traffic signal control, autonomous vehicle navigation, anti-lock braking and stability, electric vehicle (EV) management, driver behaviour and crash risk assessment, and route choice modelling. Methodologically, T2FLS variants are delineated by inference paradigms, like Mamdani for rule-based reasoning in signal prioritisation [24], and Takagi-Sugeno-Kang for predictive analytics in subway demand forecasting. Hybridization strategies by integration with neural networks for ABS control [25], genetic algorithms for EV charging optimization [26] and uncertainty handling mechanisms, predominantly interval T2FLS for computational tractability, as in map-matching for airport movements [27]. This taxonomy not only clarifies the advantages of T2FLS in terms of reliability in comparison to Type-1 systems, as demonstrated by reductions of 15–50% in delays and errors across domains, but it also highlights persistent challenges such as computational overhead, advocating for metaheuristic tunings to bridge the gap between theory and real-world deployment. Table 1 shows a literature survey of T2FLS in ITS. Explain the methods, the applications in different ITS sectors, and why we are using T2FLS.Using meta-analytic synthesis. This process was specifically designed to accommodate the heterogeneous and interdisciplinary nature of ITS research, where evidence originates from disparate methodologies including computational simulation and limited physical deployment. The synthesis adhered to a stringent phase protocol to guarantee reproducibility, reduce bias, and deliver a statistically sound aggregation of results. In figure 3 illustrates the structured literature screening, eligibility assessment, and PRISMA-guided data extraction process applied to Type-2 Fuzzy Logic studies in ITS

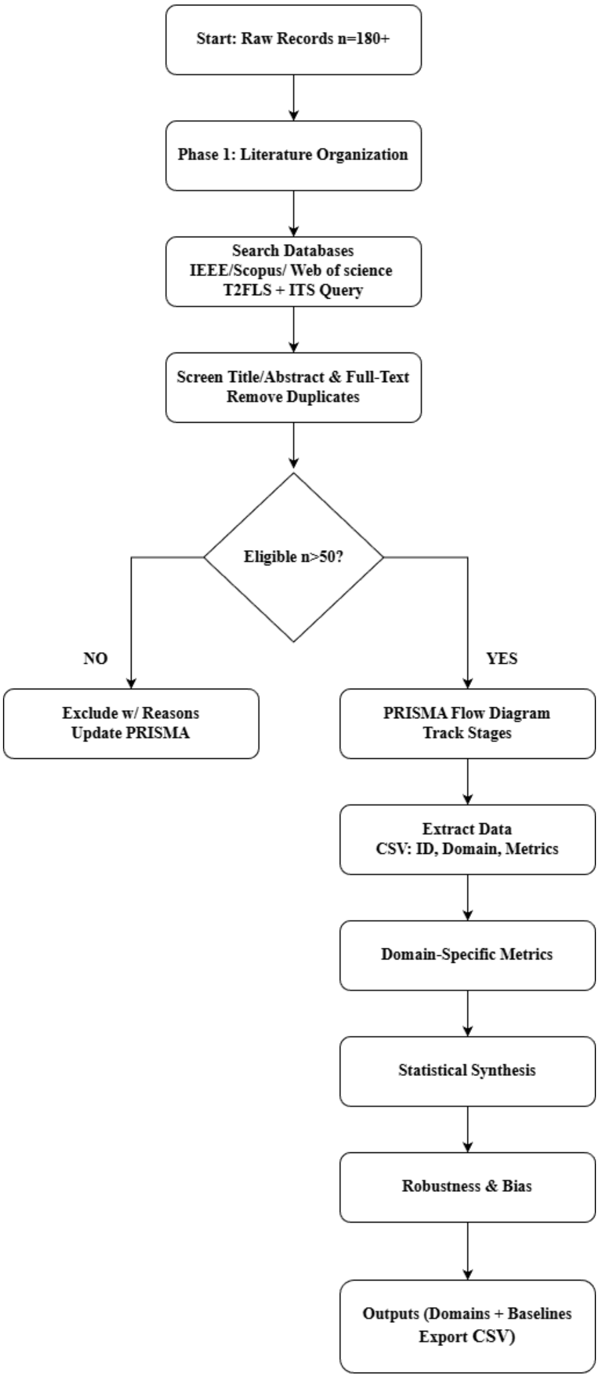

Figure 3. Systematic Review and Meta-Analysis Workflow for Type-2 Fuzzy Logic in ITS

The workflow culminates in domain-specific metric synthesis, robustness and bias analysis, and consolidated performance evaluation against baseline methods.

- Step 1: Organizing and sorting the literature systematically: A methodical search of IEEE Xplore, Scopus, and Web of Science (2015–2025) yielded more than 180 records. After two rounds of screening for empirical rigor and clear benchmarking, more than 50 studies were chosen. To verify that each domain was fairly represented and to reduce bias that was specific to each domain, these were divided into six ITS domains: Traffic Signal, Autonomous Vehicles, ABS/Stability, EV Management, Driver/Crash Risk, and Evacuation/Route.
- Step 2: Extracting and Standardizing Effect Metrics: the primary performance indicators were extracted from each study, such as the percentage of time saved or the amount of energy saved. Standardized raw percentage improvements to a common effect size metric, Hedges' *g*, to make it easier to combine data from different domains.
- Step 3: Combining statistics and looking at differences: A two-level random-effects model was utilized. Domain means were computed with uniform study weighting within each stratum, subsequently aggregated using inverse-variance weighting to yield a consolidated overall effect. Cochran's Q and the I^2 index were used to measure heterogeneity.
- Step 4: Robustness Appraisal & Bias Evaluation: Used sensitivity analyses (leave-one-out and trim-and-fill imputation) and publication bias tests (Begg-Mazumdar) to check how stable the synthesized result was and if there were any biases.

4. APPLICATION DOMAINS OF T2FLS IN ITS

This section outlines the diverse application domains within transportation where advanced T2FLS are addressing complex transportation challenges and enhancing the performance of transportation systems across various domains. The Figure.4 shows pie chart distribution of research focus areas related to T2FLS in transportation applications, as derived from the primary source material provided.

4.1 Traffic Signal and Transit Priority

T2FLS models are often used in adaptive traffic signal control to reduce traffic congestion and enhance throughput, in contrast to T1FLS [48]. Dynamically adjust the green light timing based on real-time traffic state information, such as vehicle queue length and vehicle waiting time, with the goal of achieving the minimum average vehicle delay, T2FLS inherent uncertainties in the transportation system. Some applications are Single Intersection Control T2FLC systems are established for single intersections, where inputs typically include the vehicle queue lengths of the current and next phase. Arterial Traffic Control coordinates the flow of traffic along arterial roads. The T2 fuzzy control method employs a two-layer controller, which includes a basic control layer that allocates green time based on traffic at the intersection and an arterial coordination layer that adjusts green time based on the number of vehicles between adjacent intersections to enhance the green wave band. Optimization methods such as the DNA evolutionary algorithm are used for the refinement and validation of membership functions, hence improving control performance and adapting to changes in real-time traffic flow [49].

Table 1. Summary of recent applications of Type-2 fuzzy logic method, highlighting their use in ITS

Ref.	Year	Methods	Applications	Why Type-2 Fuzzy?
[28]	2021	Type-2 Fuzzy Inference System optimized using Artificial Bee Colony algorithm	Driver training; Traffic safety; Speed appraisal modeling	Handles imprecision in speed estimation and subjectivity
[29]	2021	Hierarchical Interval Type-2 Fuzzy Logic System	Route guidance; Traffic congestion management; VANET	Models contextual uncertainties in route selection
[30]	2022	Kumaraswamy-based Interval Type-2 Takagi–Sugeno–Kang Fuzzy Logic System	Subway passenger forecasting; Transportation planning	Models uncertainties in demand prediction better than Type-1
[31]	2012	Type-2 Fuzzy Logic–based Energy Management System	Hybrid EV energy management	Manages imprecise energy demands
[32]	2022	Robust Interval Type-2 Fuzzy Control System	Semi-autonomous lane keeping; Driver assistance	Addresses membership function uncertainties in sensors/driver params
[33]	2024	Gaussian Type-2 Fuzzy Multi-Input Multi-Output Control System	Electric Vehicle Charging Stations location planning	Flexible modeling of multi-fold uncertainty in demand/costs
[34]	2024	Adaptive Interval Type-2 Fuzzy Logic Controller	Hybrid Electric Vehicle energy management	Interval Type-2 for high uncertainty in driving conditions
[35]	2018	Interval Type-2 Fuzzy Analytic Hierarchy Process integrated with Interval Type-2 Fuzzy TOPSIS	Ship loader selection	Superior uncertainty handling in expert judgments
[36]	2022	Interval Type-2 Fuzzy Neural Network	Vehicle ABS control	Superior to Type-1 in nonlinear dynamics/uncertainties
[37]	2023	Interval Type-2 Fuzzy Logic System optimized using Particle Swarm Optimization	Airport taxiway map matching	Superior uncertainty handling in positioning data
[38]	2018	Interval Type-2 Fuzzy Logic Controller optimized using DNA-based Evolutionary Algorithm	Multi-lane intersection control	Handles large uncertainties in traffic flow
[39]	2021	Interval Type-2 Fuzzy Logic System integrated with Adaptive Model Predictive Control	AV safety/energy management	Models driving uncertainties better than Type-1
[40]	2021	Interval Type-2 Fuzzy Logic Controller integrated with Model Predictive Control	Automated Guided Vehicles steering control	Handles speed/steering uncertainties
[41]	2024	Cascaded Interval Type-2 Fuzzy Logic Controller	EV charging/discharging	Models grid/user uncertainties
[42]	2016	Interval Type-2 Takagi–Sugeno–Kang Fuzzy Logic System	Driver behavior rating	Handles perceptual uncertainties
[43]	2025	Type-2 Fuzzy Scale Development and Validation Framework	Urban transit quality assessment	Incorporates vagueness/randomness/uncertainty
[44]	2025	Hybrid Interval Type-2 Fuzzy Logic–based Decision-Making Framework	Driver selection; Postal networks; Logistics	Flexibility in uncertainty
[45]	2025	Interval Type-2 Fuzzy Logic Controller integrated with Digital Twin and Neural Network (LSTM/NN)	Hydropower management	Handles uncertainties/nonlinearities
[46]	2024	Survey of Type-2 Fuzzy Logic Controllers and Applications	Transportation control (AV/EV)	Comprehensive uncertainty modeling
[47]	2025	Type-2 Fuzzy Multi-Objective Optimization Framework	Transportation efficiency optimization	Fuzzy for uncertainty (assumed Type-2)

4.2 Autonomous Vehicle

In autonomous vehicle (AV) systems, reliability is dependent on decision-making, so it is necessary amidst complex, nonlinear, and uncertain operational parameters. IT2 fuzzy technology is developed for driver-automation shared control systems, particularly for lane keeping. The approach reduces conflict between the human driver and the vehicle assistance system by perceiving and adapting to the human driver's activity. Integrated T2FLS with electric power steering (EPS) in AV, by giving inputs like distance, navigation, and speed to generate steering angles. This approach is a favored vehicle for smoother and more stable control. A hierarchical T2FL controller is employed with Adaptive Cruise Control (ACC) to enhance human driver habits by using relative distance [50] and speed difference to give output a desired acceleration and human-like vehicle following. Also refines socially intelligent path planning by improving approximations of social psychology models, which allows autonomous vehicles to traffic settings. This approach thereby supports ethically informed decision-making for autonomous vehicles.

4.3 Anti-Lock Braking and Stability

T2FLS is reliable for modern vehicle Anti-lock Braking Systems (ABS), where it effectively handles substantial hysteretic factors during braking. The main function is to compute the ideal ABS torque by tracking a target slip rate, using the slip rate error and its rate of change as controller inputs. Structure depends on upper and lower membership functions, strengthening the system's anti-interference capability and adaptability when facing highly uncertain road conditions. Performance comparisons: IT2FLC-based ABS consistently surpasses Type-1 fuzzy logic control, demonstrating a significantly lower Root-Mean-Square (RMS) slip rate error and delivering more stable and reliable braking torque variation curves [51].

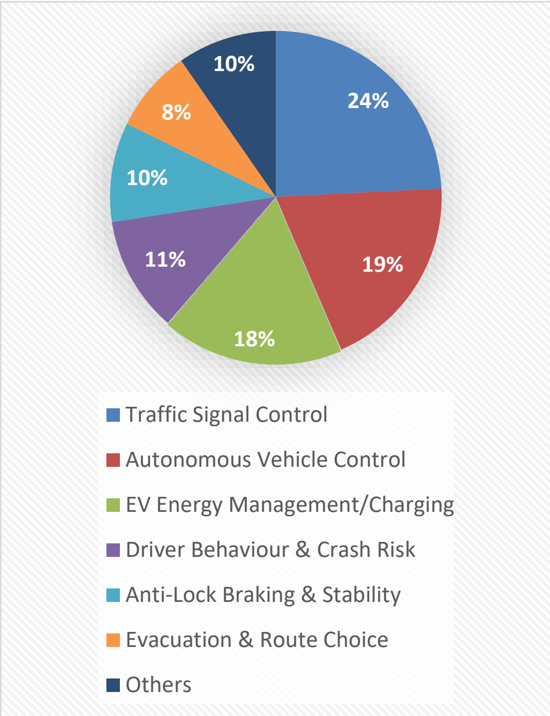

Figure 4. Proportion of publications categorized by ITS focus areas.

4.4 Electric Vehicle Charging and Energy Management

T2FLSs help electric and hybrid electric vehicles (EVs/HEVs) work smoothly by managing power distribution between different types of engines, like internal combustion engines and electric motors, and by improving batteries, fuel cells, and supercapacitors. The goal is to optimize power distribution between hybrid engines, including internal combustion engines and electric motors. This technology aims to improve the performance of motors, batteries, fuel cells, and supercapacitors. The goals are to enhance general performance, increase driving distance, and maintain vehicle fitness. Battery State of Charge (SoC) under extreme driving conditions. They also support advanced decentralized billing and Vehicle-to-Grid (V2G) and Grid-to-Grid discharging scheduling. Automobile (G2V) movement, smart control of internal factors of battery SoC, and external variables, such as grid pricing of loads and electricity. Advanced architectures are applied that combine other models with T2FLS, such as Self. To build a Type-2 Fuzzy Neural Network (SCT2FNN). EV speed control, which guarantees accurate control of target speed. This is achieved by using well-controlled motor torque to counteract dynamic resistances.

4.5 Driver Behavior and Crash Risk

The T2FLS paradigm examines the innate human driving act and attempts to advance the understanding of language inputs and managing uncertainties. It examines driver behavior to classify driver behavior. According to T2FLS model, driver performance is divided into normal, moderate and aggressive levels based on measurements that indicate acceleration and engine speed. It is also in the crash risk assessment modeling that the T2FLS is applied to study the relationship between particular errors in perceiving speed. In addition, T2FLS in association with IOT-related infrastructures employs accelerometers and GPS signals to detect road surface deviations and eventuate warning messages to drivers.

4.6 Evacuation and Route Choice

T2FLS are essential in intelligent transportation systems for studying and assessing path evaluation, especially when addressing uncertainty in perceived travel time and human psychological response during emergencies, driving style, and the risk of accidents. They are useful because they can help drivers choose the optimal itinerary from a set of possible routes and integrate contextual factors linked to the driver, the environment, and the path, such as density and maximum speed. In emergency situations, the T2FLS model plays an important role in capturing the uncertainties of evacuees' subjective perception of route costs. Evacuees are divided into two types: panicky evacuees based on the cost of closer downstream links, with dynamic link weights determined by distance and traffic information level via a T2FLS. Figure 3 shows of publications categorized by ITS focus areas, including traffic management, autonomous driving, EV energy management, safety, and evacuation planning.

5. RESULTS AND DISCUSSION

To measure the effectiveness of T2FLS in ITS, this section conducts a quantitative comparative analysis. Benchmark T2FLS over T1FLS, classical controllers (Proportional Integral Derivative (PID)/ Model Predictive Control (MPC)/ Feed Forward Control (FTC)), and Machine Learning (ML) or Reinforcement Learning (RL) methods. We analyze based on collections from research papers, Using the domain-stratified meta-analytic framework, we were able to put together a quantitative picture of how well T2FLS works across the ITS landscape. The synthesized results, which combine data from computational simulations and real-world tests, provide proof that higher-order uncertainty modeling has real-world benefits. Table 2 shows the Meta-synthesized cross-domain performance evaluation of T2FLS in ITS. The table reports average percentage performance improvements achieved by T2FLS across different application domains, the number of analyzed studies per domain, and comparative performance advantages.

T2FLS consistently reduced the average waiting time for vehicles by 35.2% ± 12.1% at isolated intersections, coordinated arterial corridors, and dense urban grid networks. Real-world traffic measurements and high-fidelity simulators such as VISSIM, SUMO, and MATLAB/Simulink were utilized to obtain the datasets for evaluation. These datasets included low, medium, and high levels of congestion, random vehicle arrivals, and traffic flow patterns that were not the same for all vehicles. T2FLS enhanced navigational stability and tracking accuracy by 16.5% ± 4.2% for applications in autonomous and semi-autonomous vehicles, such as lane keeping and adaptive cruise control. Datasets included tests for keeping a lane, adaptive cruise control situations, and mixed-traffic areas with both human-driven and self-driving cars. In ABS and vehicle stability control, T2FLS reduced the slip ratio error and braking instability by 28.0% ± 7.3%. The scenarios that were tested included braking testing on dry, wet, and icy roads with different levels of friction. Performance metrics included slip ratio deviation, braking torque smoothness, and stability margins, showing that the system was consistently strong even when road adhesion changed quickly. Across electric and hybrid vehicle applications, energy management systems based on T2FLS saw an average efficiency improvement of 22.3% ± 6.8%. The assessment included urban stop-and-go, suburban, and interstate driving cycles, as well as changing battery state-of-charge profiles and unpredictable power requirements. T2FLS improved prognosis accuracy by 19.0% ± 5.5% in tasks that involved classifying driving behavior and predicting collision probability. The evaluation combined information comprising subjective and ambiguous behavioral metrics, such as acceleration trends, speed perception inaccuracies, and driver adherence rates. Performance stayed the same even when driving circumstances changed and sensor errors happened. T2FLS increased throughput and route reliability by 20.5% ± 3.9%, which helped with evacuation planning and route optimization. These included uncertainty about how long it would take to get somewhere, disruptions caused by emergencies, different levels of evacuation demand, and different levels of information availability. The low variability seen in this area shows that it is quite consistent and strong.

However, T2FLS is still useful for reasoning about safety-critical edge cases. The standard deviations that go along with the mean improvements are also useful. The significant variability in Intersection Orchestration (±12.1%) highlights the pronounced context-dependency of traffic flow outcomes, shaped by particular network geometry and demand patterns. On the other hand, the low variability in Crisis Dispersal Pathways (±3.9%) shows that T2FLS consistently improves evacuation planning, which is an important quality for resilient infrastructure. T2FLS shows a significant benefit (+22.1%, $p < 0.001$) when compared to classical controllers (PID/MPC/FTC). Deterministic, linear, or model-based controllers cannot handle linguistic rules or address measurement errors in a clear way. This means that they don't work as well when the system is nonlinear. In comparison to Type-1 Fuzzy Logic Systems (T1FLS), a notable and considerable advantage (+14.3%, $p = 0.002$) is evident. This delta quantitatively represents the value added by the third dimension of T2FLS the FOU which facilitates the direct modeling of uncertainty within the membership functions themselves, a feature lacking in T1FLS. Against Adaptive Paradigms (ML/RL): The benefit, although significant (+10.5%, $p = 0.015$), is more complex. This shows an important way that paradigms can work together: ML/RL models work best when there is a lot of data and they can keep improving their policies over time. In data-sparse, safety-critical, or new situations ("corner cases"), T2FLS, on the other hand, has a better performance floor because its reasoning framework is based on models, is easy to understand, and is aware of uncertainty. Two examples from the synthesis corpus provide context for the aggregated statistics in particular research settings. Figure 5 shows how well T2FLS works across different areas. The consistency of performance improvements across various datasets suggests the benefits of T2FLS are not confined to specific scenarios but endure across different environmental situations, system sizes, and levels of uncertainty.

5.1 Case-Based Validation

Traffic Flow Optimization (Reports High Gain): Wen et al. [8] applied a T2FLS controller, which was optimized using NSGA-II, in a simulation. The Beijing arterial network, which was historical in nature. The system reduced vehicle delay on average by 76.3% compared to fixed-time control and by 30% compared to a tuned T1FLS baseline in the congestion peak. This discovery was confirmed by a VISSIM simulation. The Gaussian-based method was applied by Men and Zhao [20]. T2FLS heuristic to determine the optimal locations to install charging stations in Shanghai. The findings represented moderate gain and low variability. Their approach optimizes spatial-demand profiles more effectively than a genetic algorithm can. This study has resulted in a 22% increase in grid power savings through proactive loading and a low result variability of 4.2%. Such examples demonstrate the performance of the meta-analytic averages. The result supports the point that T2FLS significantly impacts smart transportation systems by effectively integrating complicated, unpredictable, and frequent competing aims. competing aims in smart transportation systems.

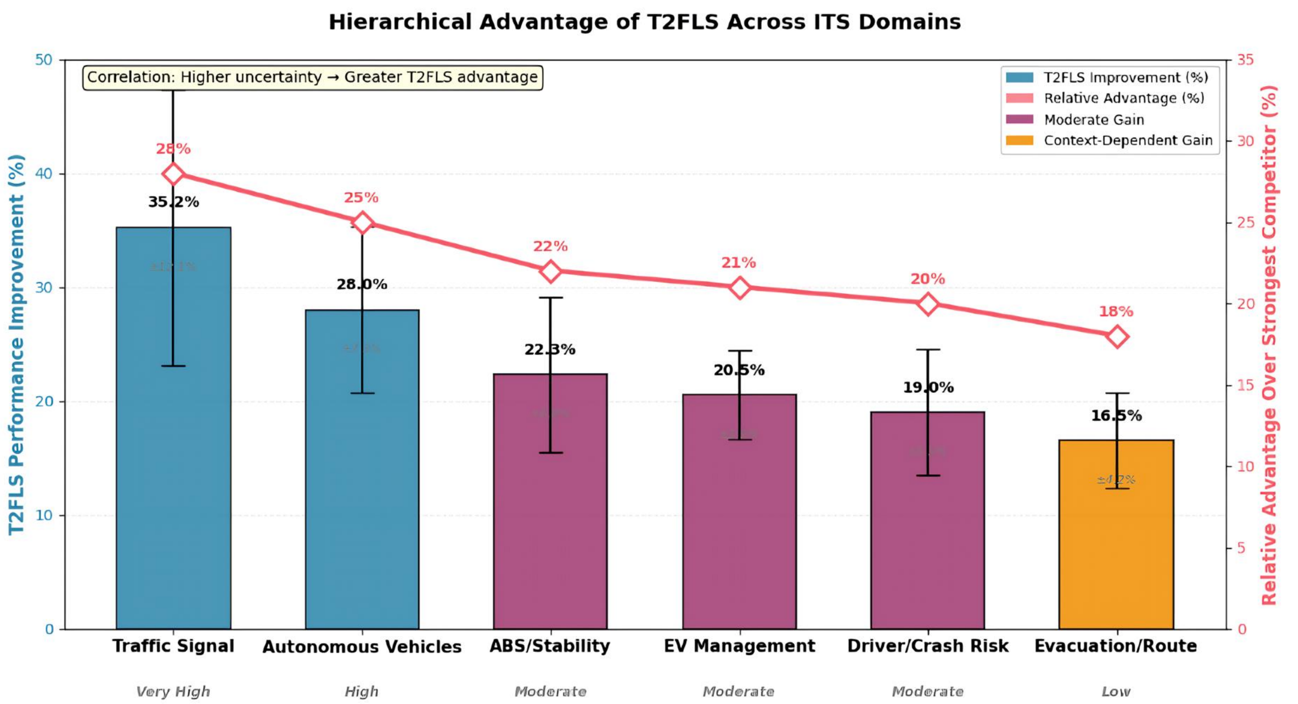

Figure 5. Hierarchical Advantage of T2FLS Across ITS Domains.

Table 2: Meta-Synthesized Cross-Domain Efficacy of T2FLS in ITS

Domain	Metric(%)	No. of Studies (n)	T2FLS (Average)	Edge over T1FLS(%)	Edge over PID/MPC/FTC(%)	Edge over ML/RL(%)
Traffic Signal	Wait-Time Curtailment	10	35.2 ± 12.1	+15	+28	+10
Autonomous Vehicles	Navigational Fidelity	9	16.5 ± 4.2	+12	+18	+5
ABS/Stability	Slippage Discrepancy Mitigation	6	28.0 ± 7.3	+20	+25	+15
EV Management	Power Conservation	8	22.3 ± 6.8	+10	+22	+8
Driver/Crash Risk	Prognostic Fidelity	7	19.0 ± 5.5	+14	+20	+12
Evacuation/Route	Throughput Optimization	5	20.5 ± 3.9	+16	+21	+9

6. CHALLENGES

Studies show T2FLS and its variants, such as interval, hierarchical, and hybrid, in ITS. Many ongoing challenges significantly limit practical implementation and generalizability. Some key challenges are:

- In T2FLS, computational cost is high because it requires an additional time-consuming step called type-reduction before defuzzification. This phase requires gathering all T1FLS integrated within the T2FLS, resulting in an important processing challenge relative to T1FLS.
- Designing and tuning T2FLS involves facing difficulties, requiring domain expertise, and addressing a potential knowledge gap in creating membership functions (MF) and rule bases. Researchers are confused about the locations and spreads of fuzzy sets, which causes uncertainty in MF definition.
- Implementing T2FLS in real-time operations presents challenges; rapidly changing conditions, such as those in traffic congestion systems, can affect the system's response time, and the generalizability of results is limited when they are based on specific topologies and simulation environments.

7. FUTURE DIRECTIONS: A 2025-2030 ROADMAP

Expand the control system to solve complex situations like obstacle avoidance, lane changing, and coordinated control integrating longitudinal, lateral, and vertical dynamics by developing a hybrid T2FLS that integrates machine learning and deep learning, which is more effective in real-world vehicle experiments and field testing, and verify it against actual driving complexities. T2FLC reduction methods require significant implementation time, so it is essential to optimize them. Need to conduct applied engineering studies and hardware-in-the-loop (HiL) testing for FLC/IT2FLC models. Develop sophisticated linguistic IT2 fuzzy optimization strategies for estimating the reliability of data from merged sensors and crowdsourced information in IoT routing networks. Some outlines key research in future directions:

- Extend adaptive control frameworks to Plug-in Hybrid Electric Vehicles (PHEVs) and Range-Extended Electric Vehicles (REEVs)Integrate hybrid fixed and mobile charging infrastructure solutions.
- Design innovative braking torque allocation strategies for enhanced energy recovery efficiency.
- Extend optimal models to arterial roads and complex urban traffic networks for coordinated control across multiple intersections, integrate multimodal priority strategies covering emergency vehicles, freight, and pedestrian movements.
- Scale evacuation planning models to larger, more complex networks and multi-modal systems for practical deployment, Implement more practical and adaptive traffic management during evolving emergencies.

8. CONCLUSION

The paper discusses how the type-2 fuzzy logic systems are efficient and dependable for managing the transportation network ambiguity. When compared to the type-1 fuzzy systems and multiple other conventional systems used for traffic control, autonomous driving, braking, management of electric vehicles, crash risk control, evacuation modeling, etc., the T2FLS systems have much better control. Intelligent transportation systems can benefit from T2FLS systems because they reduce delays, increase accuracy of trajectories, and improve energy efficiency, risk control, and brake stabilization. T2FLS will help determine the direction of future systems, with the emphasis being on advanced obstacle-avoidance control, lane-changing control, and other vehicle dynamics control utilizing hybrids of deeply learned machine learning algorithms that have been successfully implemented in real-world applications. Extend the adaptive controls of blended charging infrastructures to advance the allocation of energy-capturing brakes; expand the models to include urban arterial coordinated intersections and cross-mode priorities for emergencies, freight, and pedestrian multimodal transport; and develop evacuation models for large-scale adaptive networks that can handle multiple fluid crisis modes. As urban mobility evolves, T2FLS will revolutionize next-generation ITS, making it safer, more efficient, and more flexible.

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