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Review

Urban Day-to-Day Travel and Its Development in an Information Environment: A Review

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Abstract: Urban day-to-day travel systems generally exist in various types of cities. Their modeling is difficult due to the uncertainty of individual travelers in micro travel decision-making. Moreover, with the advent of the information age, intelligent connected vehicles, smartphones, and other types of intelligent terminals have placed urban day-to-day travel systems in an information environment. In such an environment, the travel decision-making processes of travelers are significantly affected, making it even more difficult to give theoretical explanations for urban day-to-day travel systems. Considering that analyzing urban day-to-day travel patterns in an information environment is of great significance for governing the constantly developing and changing urban travel system and, thus, of great importance for the sustainable development of cities, this paper gives a systematic review of the theoretical research on urban day-to-day travel and its development in an information environment over the past few decades. More specifically, the basic explanation of an information environment for urban day-to-day travel is given first; subsequently, the theoretical development of micro decision-making related to individual day-to-day travelers in an information environment is discussed, and the theoretical development related to changes in urban macro traffic flow, which can be recognized as the aggregation effect formed by individual micro decision-making, is also discussed; in addition, the development of understanding different types of traffic information that travelers may obtain in an information environment is discussed; finally, some important open issues related to the deep impact of information environment on urban day-to-day travel systems that require further research are presented. These valuable research directions include using information methods to fit day-to-day travel patterns of cities and implementing macro and micro integrated modeling for urban day-to-day travel systems based on complex system dynamics and even quantum mechanics.

Keywords: urban day-to-day travel; information environment; theoretical development; travel system modeling; micro travel decision-making; macro aggregation effect

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1. Introduction

Urban day-to-day travel systems always coexist with cities [1]. With the continuous development and popularization of various transportation tools, the travel dimensions and complexity of participants in urban travel systems are constantly increasing. Moreover, with the advent of the information age, intelligent connected vehicles, smartphones, and other types of intelligent terminals have placed urban day-to-day travel systems in an information environment. In such an environment, the travel decision-making processes of travelers are significantly affected, and new changes are undoubtedly brought to urban day-to-day travel systems [2–4]. Therefore, analyzing urban day-to-day travel patterns in an information environment is of great significance for governing the constantly developing and changing urban travel system and, thus, of great importance for the sustainable development of cities.

Scholars have already conducted extensive theoretical research on micro travel decision-making of urban day-to-day travelers and macro road traffic flow changes, making necessary contributions to the modeling of urban day-to-day travel. However, there are few studies that systematically analyze the methodologies that have been proposed by scholars and organize the development of these methodologies. In addition, the advent of the information age is bringing and will continue to bring new impacts on the day-to-day travel decisions of travelers by providing various types of travel reference information, which will become increasingly important for the development and change in urban day-to-day travel systems in the future. In this context, conducting a phased review of the theoretical research on urban day-to-day travel and the impact of the information environment on it is of great importance for grasping the effective analytical methodology of day-to-day travel patterns in the information age.

This paper has tried to give a systematic review of the theoretical research on urban day-to-day travel and its development in an information environment and has also tried to point out several challenging open issues for the theoretical development of urban day-to-day travel systems for the first time. The structure of this review is arranged as follows. Section 2 gives a basic explanation of the information environment for urban day-to-day travel. Subsequently, Section 3 focuses on the theoretical development of micro travel decision-making related to day-to-day individual travelers in an information environment. Section 4 mainly includes theoretical development on macro traffic flow, which is deeply impacted by those micro decisions made by travelers. The development of understanding different types of traffic information that travelers may obtain in an information environment is discussed in Section 5. In addition, some important open issues that require further research are presented in Section 6. Section 7 provides a summary of the entire research content. The overall framework of this paper can be found in Figure 1, and the abbreviations mentioned in this paper can be found in Table 1.

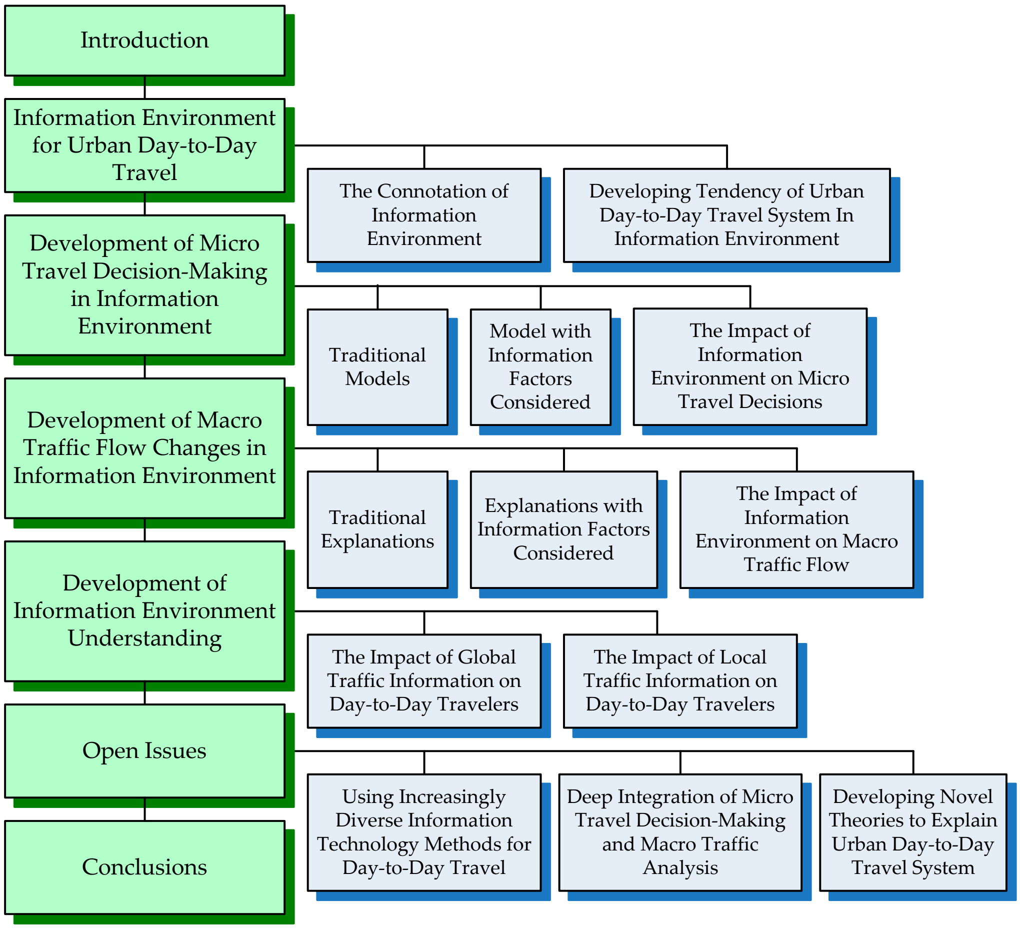

Figure 1. The overall framework of this review.

Table 1. The list of abbreviations that appear in this review.

Abbreviation	Definition	Abbreviation	Definition
ABM	Activity-based model	ARCHs	Autoregressive conditional heteroskedasticity family models
ART	Approximate reasoning for transportation	ASL	Arrive-stay-leave
ATC	Automatic toll collection	ATIS	Advanced traveler information system
AV	Autonomous vehicle	BDI	Beliefs, desires and intentions
BRUE	Bounded rationality user equilibrium	CCL	Congestion-based conditional Logit
FCD	Floating car data	FVP	Frequently visited point
GPS	Global positioning system	HMM	Hidden Markov model
HV	Human-driven vehicle	ICSS	Iterative cumulative sums of squares
ICT	Information and communication technology	IRL	Inverse reinforcement learning
ITS	Intelligent transportation system	LBS	Location-based service
LCL	Length-based conditional Logit	LRP	Linear rewards and punishments
MFD	Macroscopic fundamental diagram	MFG	Mean field game
MILP	Mixed-integer linear programming	MNL	Multinomial Logit
MPC	Model predictive control	MSD	Mobile signaling data
NMHE	Nonlinear moving horizon estimation	NP	Non-deterministic polynomial
OD	Origin and destination	PUE	Pessimistic user equilibrium
RAP	Resident activity pattern	rePRAP	Relative proportion-based route adjustment process
RGS	Route guidance system	RL	Reinforcement learning
RP	Revealed preference	RTW	Return to work
RUE	Rationality user equilibrium	RUM	Random utility model
SCD	Smart card data	SDSUE	State-dependent stochastic user equilibrium
SLA	Stochastic learning automata	SP	Stated preference
SUE	Stochastic user equilibrium	TDM	Travel demand management
TTV	Travel time volatility	UE	User equilibrium
VI	Variational inequality	VMS	Variable message sign

2. Information Environment for Urban Day-to-Day Travel

2.1. The Connotation of Information Environment

Information factors have existed since the birth of urban day-to-day travel systems. The travel experience of travelers in route choice is just a kind of information that will affect their micro decision-making regarding their next travel decision-making. After travel decisions have been made, new traffic information will emerge in urban day-to-day travel systems, and travelers as individuals will also acquire new travel experience information. However, these pieces of information are relatively isolated. The emergence of the information environment is derived from the continuous development of information and communication technology (ICT). With the help of ICT, urban day-to-day travelers can access traffic information through various types of public information dissemination channels.

During the past few decades, the emergence of intelligent transportation systems (ITSs) and various types of advanced traveler information systems (ATISs) has already greatly changed the behavior of urban day-to-day travel and has put urban day-to-day travel systems in an information environment [5]. Furthermore, with the widespread popularity of smartphones and intelligent terminals, the integration of satellite positioning, WiFi, and cellular mobile networks can provide more accurate positioning information and higher quality travel route suggestions for day-to-day travelers, including the design of travel routes to avoid congestion, and, thus, can surely bring profound changes to the traditional urban day-to-day travel system [6]. At the same time, intelligent terminals like smartphones can also provide a powerful location-based service (LBS) push for travelers, thereby playing an important role in changing travel route choice strategies and even adjusting the purpose of the travel process [7–13]. As a result, the intensity and spatiotemporal evolution of travel activities on some road sections have also changed greatly [9]. The information environment has already become the “standardized configuration” of contemporary urban day-to-day travel systems.

2.2. Developing Tendency of Urban Day-to-Day Travel System in Information Environment

As information environments have become ubiquitous in urban day-to-day travel systems, travelers can obtain travel-related reference information more and more conveniently through various means. Thus, their travel behaviors can be changed and, thus, always affect the macro urban day-to-day travel system. Kwan has pointed out that the information environment has changed the way time is utilized and has enhanced the mobility of macro roads. It has been pointed out that the impact of ICT on people has blurred the concepts of work and home, and the statistical theoretical framework and distance calculation based on fixed origin and destination (OD) may no longer be applicable in understanding urban day-to-day travel patterns [14]. Line et al. have explained the shopping activity travel route choice behavior of part-time mothers under the impact of ICT through quantitative logs and individual interviews. They found that ICT can not only change the travel time arrangement of this specific population but can also analyze the travel characteristics of this population well [15]. It can be seen that the information environment has changed urban day-to-day travel patterns and has certainly brought significant development and change to urban day-to-day travel systems.

3. Development of Micro Travel Decision-Making in Information Environment

Micro travelers are the actual participants in urban day-to-day travel systems. Their day-to-day travels often have a group of definite OD points, but the travelers have strong randomness in the decision-making for specific transportation modes and routes [16–22]. On some level, the process of day-to-day travel decision-making can be seen as a continuous game between travelers to achieve their travel goals by spending a shorter travel time. This game process has always existed, even before the emergence of the information environment, and can be summarized in Figure 2.

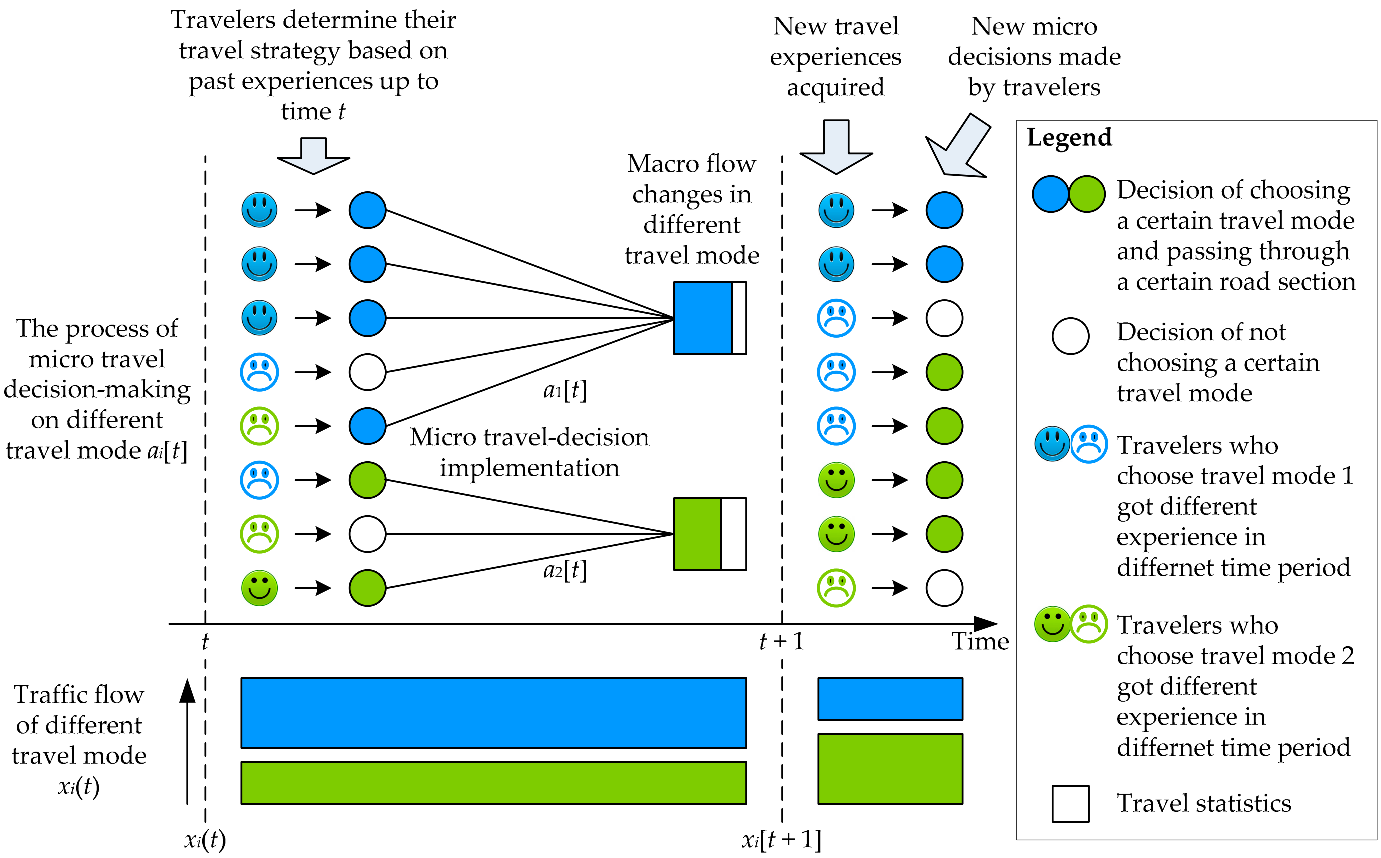

Figure 2. Process abstract of micro travel decision-making.

3.1. Traditional Models

3.1.1. Deterministic Models

The representative type of model for micro decision-making in the early stage of studying urban day-to-day travel is the deterministic model. This type of model believes that during the process of day-to-day travel, specific decisions are always made for several consecutive days, and travelers must convert their decisions with a certain ratio based on the travel effect among certain choices [23]. Yang et al. have pointed out that deterministic models for describing changes in micro decision-making strategies and dynamic behavior adjustments can be roughly divided into five types: gravity flow model, percentage conversion model, network trial and error process model, projection dynamic system model, and evolutionary traffic dynamic system model [24].

The relevant research conducted by Smith is the simplest gravity flow model with a simple assumption of the micro travel decision conversion process just relying on the theory of gravity flow [25].

After the proposal of the gravity flow model, Smith proposed a dynamic traffic flow allocation calculation method based on the Lyapunov function. In this method, the concept of travel cost is introduced, various costs involved in travel are quantified, and a percentage conversion model is applied to the transition from high travel cost to low travel cost in the micro decision-making transformation process [26]. Subsequently, Smith et al., Huang et al., Peeta et al., and Mounce et al. have discussed and improved the percentage conversion model, making it an important theoretical method for explaining the deterministic model of micro travel decision-making [27–31]. Based on this method, Zhu et al. have proposed a relative proportion-based route adjustment process (rePRAP) and have pointed out that high-cost routes can quickly shift towards low-cost ones [32]. Alibabai et al. have characterized travelers as sheep-type and fox-type thinkers and have pointed out that there are thresholds for their proportion in overall travel [33].

Friesz et al. have provided the theoretical prototype of a network trial and error adjustment strategy for discrete-time micro route choices; the strategy focuses more on the dynamic changes in the flow of travel routes and their impact on micro route choice decision-making [34]. Subsequently, Jin and Guo et al. have further improved the day-to-day micro route choice model, especially for the dynamic allocation of micro route choices under the impact of the flow of travel routes in the macro road network and have discussed the dynamic evolution process of route choices [35,36].

The projection dynamic system model is similar, in principle, to the percentage conversion model, which studies the batch conversion of individual micro route choice strategies under the impact of macro road traffic flow distribution. Zhang et al. have proposed a projection dynamic system model based on the minimum norm projection operator to simulate changes in micro route choice strategies over a continuous time axis [37]. One year later, Nagurney et al. have further discussed the model proposed in the literature [37] and have concluded that although the continuous time projection dynamic system model can better describe the changes in micro route choices, it still has some drawbacks: firstly, the route adjustment in the continuous time model is not realistic for day-to-day travel, whereas the discrete time model can better describe the day-to-day changes in micro route choices; secondly, the understanding of population attributes in the model in literature [37] is homogeneous, and a new decentralized model needs to be introduced to simulate individual differences among different travelers [38]. To address the above drawbacks, Nagurney et al. have developed a new projection dynamic analysis method based on variational inequality (VI) in discrete spacetime and have used the Euler method to solve the projection dynamic system problem in discrete time, achieving good results [38]. Then, Zhong et al. further extended the projection dynamic system to a projection like Newtonian inertial dynamics, describing the day-to-day travel system as a second-order gradient dissipative dynamic system. They discussed the convergence of the proposed model and the equivalence between its fixed points and the equilibrium of elastic demands from travelers [39].

Evolutionary traffic dynamic system models are more concerned about the changing processes of macro road networks under the impact of day-to-day micro route choice strategies. Bertsekas et al. have attempted to use the concept of dynamic systems to simulate the dynamic route trajectory of continuous traffic flow [40]. Davis et al. have confirmed the randomness of micro route choices and have demonstrated that deterministic evolutionary traffic dynamic system models can serve as reasonable approximations of stochastic dynamic processes; thus, they have proposed an evolutionary traffic dynamic system model based on transformation matrices [41]. In addition, Sandholm has also proposed a model case of evolutionary traffic dynamic systems based on game theory, taking the day-to-day travel system in which numerous participants participate in the travel game as an example [42].

3.1.2. Stochastic Models

In the study of micro travel decision-making, many scholars also believe that the decisions made by each individual in urban day-to-day travel systems under the impact of multiple complex factors have strong randomness. Therefore, a large number of stochastic models have been proposed to describe micro travel decision-making in day-to-day travel, including the random utility model (RUM), the stochastic learning model, the Markov random state transition theory-based model, and the reinforcement learning (RL)-based model.

In the study of RUM, Lotan has applied the approximation reasoning for transportation (ART) model to describe the route choice behavior of travelers and has also used RUM to model the same problem, focusing on the behavioral differences among travelers with different levels of familiarity with the road network [43].

In terms of research on stochastic learning models, Ozbay et al. have effectively utilized the theory of stochastic learning automata (SLA) to model the micro route choice behavior of urban day-to-day travel; the model uses discrete time to describe travel behavior day after day. In terms of implementing stochastic learning in the model, a linear reward and punishment (LRP) function has been used to simulate the route choice learning and decision-making process for individuals on each travel day [44,45].

In the research of models based on Markov random state transition theory, Hazelton has made a beneficial attempt to simulate the discontinuity and randomness of day-to-day route choice adjustment by travelers by using Markov processes [46]. According to the fact that micro route choice decisions for day-to-day travel rely on previous traffic conditions, Hazelton et al. have also used Markov analysis methods for macro traffic flow allocation based on micro route choice [47].

For research of models based on RL, Wahba et al. have considered discretized departure time while modeling the micro route choice process. Based on Markov processes and RL theory, they have effectively simulated micro route choice models for day-to-day travel [48,49]. In addition, Zolfpour-Arkhlo et al. have specifically studied the Q-factor dynamic evaluation model for micro route choice for day-to-day travel based on motor vehicles. By continuously learning the weights of elements like safety and climate factors in the road network that affect micro decision-making, travel strategies for individuals are adjusted [50].

If the performance of these five deterministic models mentioned in Section 3.1 and the above four stochastic models for micro decision-making in day-to-day travel are compared, it can be found that their complexity and closeness to the description of real travel states are strongly correlated, as shown in Table 2.

Table 2. Comparison of deterministic and stochastic models for micro travel decision-making.

Model Types	Models	Maturity	Model Complexity	Closeness to Real Travel States
Deterministic models	Gravity flow model [25]	In 1980s	★	★
	Percentage conversion models [26–33]	In 1980s	★	★
	Network trial and error models [34–36]	In 1990s	★★	★★
	Projection dynamic system models [37–39]	In 1990s	★★	★★
	Evolutionary traffic dynamic system models [40–42]	In 1990s	★★★	★★★
Stochastic models	RUM [43]	In 1990s	★★	★★
	Stochastic learning models [44,45]	In 2000s	★★★	★★★
	Markov random state transition theory-based models [46,47]	In 2000s	★★★	★★★
	RL-based models [48–50]	In 2010s	★★★★	★★★★

The number of "★" given in this table reflects the level of a model with certain properties: the more "★"s there are, the more complex the model is, and the closer the model is to real travel states.

3.2. Models with Information Factors Considered

As mentioned in Section 2.1, as information factors have always existed in urban day-to-day travel systems, studies in the early stages have already begun to consider various information factors, although, at that time, urban day-to-day travel systems were not put in an information environment with various types of intelligent systems and intelligent terminals. Before, during, and after the travel process, past experiences, travel mode and route choice decisions, travel time, and money costs are all important information factors that can be used in urban day-to-day travel analysis [51,52]. In addition to the deterministic and stochastic models mentioned in Section 3.1, there are also some other models that not only describe the micro-level travel decision-making process in urban day-to-day travel but also take information factors into consideration. It should be pointed out that by comparing them with traditional deterministic and stochastic models, these attempts are still attracting attention from scholars and are still in theoretical development, as they focus more on finely describing the individual differences of micro travelers.

A lot of scholars have established route choice theory models for each traveler based on utility theory, which operates on the premise that every traveler wishes to pursue utility maximization and that utility is closely related to past travel experiences and current travel state [53–59]. Based on utility theory, Fan et al. have introduced the reference dependency theory into the utility model. In their research, the day-to-day route choice behavior of travelers has been considered to follow the decision-making process based on the Logit model, and the travel cost function established using reference dependency theory has been defined as the increase or decrease in travel time perceived by travelers based on relevant reference points [60]. Li et al. have further extended the utility model to two dimensions: expected utility and perceived utility. By utilizing the differences between the two and combining the cumulative prospect theory to reflect the utility of travel routes, they have focused on analyzing the dynamic route choice-changing behavior of travelers in uncertain environments [61].

Some scholars have used stated preference (SP) and revealed preference (RP) in modeling micro travel decision-making of urban day-to-day travelers. SP- and RP-based models can effectively grasp some psychological activities and personality characteristics that are difficult to express explicitly in the data during travel processes. Khattak et al. have used the survey methods of SP and RP to study the route choice behavior of vehicles with wireless communication functions in a large city and have found that delay time information has a significant impact on the route choice behavior of travelers [62]. Abdel-Aty et al. have used a repeated SP survey method specifically targeting the impact of travel time information on route choice [55]. Cheng et al. have also used an SP survey to analyze the heterogeneity of departure time choices among passengers who choose to travel on the subway during peak hours. They have found that passengers are more sensitive to ticket prices compared to crowded travel experiences [63].

A multi-agent-based modeling approach has been considered one of the most promising attempts to model the micro travel decisions of day-to-day travel, as each agent can be aware of its initial state, changing environment information, and possible behavioral outcomes. Moreover, each agent has independent beliefs, desires, and intentions (BDI) and can make independent reactions to different information [64,65]. Similar to multi-agent-based models, RL-based models can also describe new rational travel decisions made by travelers under various information factors. They can be combined with multi-agent-based models to describe the micro decision-making process of urban day-to-day travelers, or they can be used independently. Lahkar et al. have introduced a mechanism similar to the RL algorithm into a multi-agent simulation system in which each agent follows a rule that "when a behavior triggers high feedback, the probability of making the corresponding choice during the subsequent discrete time increases"; thus, the perception of travelers on travel time and road network characteristics can be simulated [66]. Wei et al. have introduced the RL algorithm into a multi-agent simulation model where each simulated traveler can provide positive and negative feedback based on expected and perceived time. Moreover, the model has assigned different memory weights to different memory-forgetting durations based on human memory characteristics [67]. Nai et al. have proposed a hybrid policy gradient-based actor-critic generative adversarial RL model to describe the route choice strategies and optimization methods for micro travelers [68]. Zhao et al. have proposed a universal deep inverse reinforcement learning (IRL) framework for link-based route choice modeling, which combines different features of state, action, and travel context and captures the dynamic properties of micro route choice, achieving competitive interpretability of micro travel decision-making [69].

Real travel data is of greater significance for establishing models, and it supports the emergence of empirical models. Cui et al. and Kim et al. have collected long-term smart card data (SCD) from the automatic toll collection (ATC) systems of buses and subways so as to analyze the regularity and contingency in micro decision-making of travelers in their long-term changes under the influence of travel costs and travel experiences [70,71]. Huang et al. have collected trajectory data for private cars, which can identify frequently visited points (FVPs) of micro travelers, and have found that micro travelers with more FVPs have less randomness in route choice despite the influence of information factors [72]. Through real micro travel data, Hadjidimitriou et al. and Montello et al. have tried to detect spatiotemporal activity patterns and activity objectives of travelers and have found that travelers tend to choose different routes when traveling back and forth between a certain pair of OD, and this asymmetry phenomenon is very significant [73,74]. After learning this, scholars have attempted to use the behavioral patterns demonstrated in actual data to improve the traditional micro decision-making theory of day-to-day travel, integrating subjective and objective factors such as inertia, preference in route choice, and route attractiveness into the micro travel decision-making model as much as possible [75].

The above models discussed in this section with information factors considered are summarized in Table 3, in which specific information factors considered in each study are listed in detail.

Table 3. Research on micro travel decision-making with different information factors considered.

Detailed Models	Literature	Information Factors Considered				
		Past Travel Experiences	Personal Habits	Time Cost	Money Cost	Crowding or Congestion Level
Utility theory-based models	[53]			√		
	[54–61]	√		√		
SP- and RP-based models	[55,62]			√		
	[63]				√	√
Multi-agent- and RL-based models	[64,65]	√	√	√		
	[66]			√		√
	[67]		√	√		
	[68]	√		√		
	[69]	√		√		√
Empirical models	[70,71]				√	√
	[72–74]		√			
	[75]	√	√	√		√

"√" given in this table means that the corresponding information factor in that column has been considered in the research of the corresponding literature in that row.

3.3. The Impact of Information Environment on Micro Travel Decisions

As described in Section 2.1, the emergence of systems such as ITS and ATIS that employ ICT, as well as the popularity of various intelligent terminals such as smartphones, have created an information environment for urban day-to-day travel and have provided ubiquitous traffic information for travelers. The introduction of traffic information has greatly changed the behavior patterns of travelers in urban day-to-day travel systems and has formed two sets of dialectical relationships that cannot be ignored between travelers and traffic information itself. Firstly, traffic information itself has its own duality, and the acquisition of it may not always have a positive effect on travelers. Travelers can, of course, have different attitudes towards traffic information prompts; such a situation constitutes a new dimension of individual differences in travel decision-making in the information environment. Secondly, travelers and traffic information have a mutual impact on and interaction with each other. While travelers obtain traffic information and make travel decisions, they constantly create new traffic information, which will once again affect their future travel decisions. Due to the duality of traffic information itself, different scholars have presented three different attitudes when discussing the impact of traffic information on micro-level travel decisions—positive, negative, and neutral—which are summarized in Table 4.

Table 4. Research on micro decision-making of urban day-to-day travelers under the impact of an information environment.

Research Attitudes	From the Perspective of Traffic Information	From the Perspective of Travelers
Positive	Improve urban transportation conditions [76–78] Provide travel decision-making assistance [35,82–85] Reduce emissions, protect environment [83]	Willing to accept information prompts [79–81] Willing to face risk with the help of information [86] Information provided by mobile devices affects most [87]
Negative	Bad effects of improper information dissemination [88] Real road network information may not lead to best traffic distribution [95] Information prompts do not lead to traffic condition improvement [96] Better to follow intuition than follow information prompts [100]	Unwilling to accept information prompts [89–94] A majority of travelers are indifferent to information prompts [97–99]
Neutral	Interaction in social platforms is also a part of travel information [101,102] Information prompts may not always have a fixed effect [107,108] Effectiveness varies depending on the penetration rate of ATIS [109,110] Information dissemination has different strategies [111] Correct and incorrect information may both have good effects [113] Different impact of information prompts inside/outside congestion area [114]	Different attitudes towards information prompts [103–106] Differentiated information dissemination considering different personalities of receivers [112]

3.3.1. Positive Impact of Traffic Information on Micro Travel Decisions

The positive side of traffic information is undoubtedly the decision-making assistance it can bring to travelers, improving their travel efficiency and reducing travel costs. At the same time, the statistical information reflected by traffic information can also be used for scientific research. Shi et al. have used economic methods to study the effect of traffic information on improving travel efficiency, pointing out that traffic guidance information can increase the expected value of travelers in urban road networks and can reduce the expected value of transportation network operating costs [76,77]. Shi has also studied the role of traffic guidance information in accidents in urban day-to-day travel networks, pointing out that it can effectively alleviate traffic congestion [78]. Bazzan et al. have conducted a study on the impact of information received by drivers during day-to-day commuting and have pointed out that route recommendation information can effectively reduce the Braess paradox phenomenon [82]. As people have been paying more attention to environmental protection, Lila et al. have pointed out that with the changes in people's daily activities and travel behavior caused by ICT, the introduction of traffic information can also effectively reduce vehicle driving mileage and carbon emissions [83]. In terms of specific quantitative research on positive effects, Emmerink et al. have pointed out that traffic information in ATIS can help travelers reduce travel time by 5–20% in traffic congestion situations [84], Jin has pointed out that traffic guidance information can reduce travel delay by 60% in non-repetitive congestion situations [35], and Wang et al. have pointed out that traffic information prompts with expected driving time can increase the behavioral rationality of drivers by an average value of 10% [85].

Regarding the study on the positive reception of traffic information by travelers, Ben-Akiva et al. have pointed out that travelers who are willing to use traffic information often compare the degree of congestion on different travel routes and choose the most favorable travel strategy [79]. Adler et al. have collected data from 27 participants using the FASTCARS simulation system and have found that travelers who have not ever used traffic guidance information are more willing to accept it [80]. Ben-Elia et al. have pointed out that traffic information can enhance the RL effect of travelers on the macro flow state of travel routes, and with the help of traffic information prompts, travelers are more willing to face the potential high-cost risks of travel [86]. Madanat et al. have argued that, due to the higher credibility of complete and accurate traffic information, it often leads to an increase in route-changing rates [81]. Tsirimpa has found through SP experimental modeling analysis that the traffic information obtained from intelligent terminals is most likely to change the day-to-day travel behavior of travelers and even affect the arrangement of the order of travelers' daily activities [87].

3.3.2. Negative Impact of Traffic Information on Micro Travel Decisions

As mentioned at the beginning of this section, the introduction of traffic information into day-to-day travel is not totally positive, according to some practical tests. The publication of certain traffic information often has side effects on travel decisions and may not even provide significant and effective assistance for the overall governance of urban day-to-day travel systems, leading to negative attitudes among both travelers and urban traffic-governing officials towards the acceptance of traffic information.

In terms of the negative attitude of travelers towards traffic information, Mannering has pointed out that different types of day-to-day travelers have different reactions to traffic guidance information, and the general "round-trip community" often does not accept suggestions for changing travel modes in traffic information prompts [89]. Dia has established an architecture based on the trinity of "belief-demand-intention" for drivers in urban day-to-day travel systems and has found that the ways of adjusting travel strategies according to traffic information between travelers are not the same [97]. Yang et al. and Huang et al. have studied the effectiveness of ATIS in reducing total travel system costs and saving travel time and have found that the level of trust of travelers in ATIS varies from person to person. They have pointed out that there are a considerable number of travelers who are indifferent to the traffic information prompts provided by ATIS [98,99]. Subsequently, Fusco et al. have further analyzed similar OD clusters in floating car data (FCD) and have demonstrated that a considerable number of drivers are not inclined to change their choices of familiar routes [90]. Yang, Yang et al., Yin et al., and van Essen et al. have all studied the impact of users who hold a negative attitude and do not take action when faced with traffic information prompts during day-to-day travel in cities and have discussed the macro user equilibrium (UE) of urban day-to-day travel systems formed by their presence [91–94].

In terms of the potential negative impact of traffic information factors on travel, Arnott et al. have pointed out that improper traffic information dissemination can lead to excessive reaction behavior of travelers towards road conditions, resulting in even poorer traffic distribution adjustment results [88]. Wu et al. have studied the appropriate way to publish ATIS information, focusing on the relationship between the micro route choice of travelers and traffic information publishing methods. They have proposed a dynamic programming model and optimal control model, which reflects the daily process of receiving and adjusting ATIS information and tries to seek the optimal traffic information publishing strategy. Their conclusion is that in many cases, providing real road network information by ATIS cannot achieve the optimal macro traffic flow distribution [95]. In the process of improving public transportation service levels through soft transportation interventions such as traffic information prompts, Fan et al. have found that effective prompts do not necessarily imply a significant improvement in public transportation service levels in the perception of travelers [96]. Han et al. have pointed out that day-to-day travelers do not pay as much attention to whether the road network has reached its optimal state as urban traffic governing officials, and often exhibit a selfish characteristic. Therefore, the route changing suggestions provided by ITS for them cannot play any substantive role, and are even less effective than the intuition of travelers [100].

3.3.3. Dialectical Discussion of Traffic Information on Micro Travel Decisions

In the past decade, research on the impact of traffic information on day-to-day travel has become more dialectical, providing more rational judgments rather than just discussing positive or negative aspects. Some scholars believe that the attitude taken by travelers when receiving traffic information prompts may not necessarily match the favorable situation that traffic information indicates. Even for the same traveler, providing similar traffic information at different travel time points may lead to completely different decisions made by him or her. Wei et al. and Zhang et al. have pointed out that in an information environment, the interaction between travelers and their social relationships, as well as the interaction between travelers and social platforms, should also be considered important traffic information influencing factors for their travel decisions, but these influencing factors are not static [101,102]. Zhao et al. have argued that specific travelers, due to their relatively fixed day-to-day travel OD, may not adopt a fixed attitude towards traffic information as an external intervention tool that influences their decision-making, but their actual behavior always varies within a certain range [107]. Ilkhani et al. have also pointed out that under different spatiotemporal situations, different types of traffic information, such as weather conditions and congestion states, usually have different impacts on travelers with different personalities [108]. Zhou et al. and Liu et al. have mainly discussed the impact of traffic information publishing on the overall urban day-to-day travel system under different penetration rates of ATIS; their conclusion has shown that it is not that the higher the popularity of ATIS, the better. When its market penetration rate is 75%, the least fluctuation in traffic flow can be achieved, and the macro road network can also reach the most stable state [109,110]. Rahimi-Farahani et al. have studied different strategies for traffic information publishing using the route guidance system (RGS), such as minimizing the total travel time of travelers or minimizing the total route length of travelers. They have pointed out that the advantages and disadvantages of the two strategies should be balanced with the goal of reducing overall urban congestion as well as individual unfairness [111]. Han et al. have dialectically pointed out that both accurate and inaccurate traffic information have their own applications, and sometimes, completely accurate traffic information does not significantly reduce commuting costs for specific urban road network capacity and travel group characteristics [113]. Yu et al. have studied the effectiveness of publishing traffic information within and outside day-to-day traffic congestion areas in cities and have found that publishing congestion information in congestion-adjacent areas may reduce the overall performance of urban road traffic networks, while publishing congestion information one to two blocks away can improve the travel time of 75% of travelers [114].

Undoubtedly, there are different attitudes of day-to-day travelers towards traffic information prompts, which need to be viewed dialectically. Moreover, there are also differences in the rationality of traffic information published, and some scholars have conducted exploratory research to address this issue. Diop et al. have specifically focused on the information prompts of variable message signs (VMSs) in cities, attempting to objectively quantify travelers' attitudes towards traffic information publishing from several dimensions, such as familiarity with travel routes, quality of information published, and attitude towards changing routes [103]. Meneguzzer has pointed out that different travelers have different attitudes towards traffic information, and because each traveler has different lengths of memory time for past travel experiences, they often hold different degrees of critical attitudes when examining traffic information prompts [104,105]. Similar to the literature [105], Ayaz et al. have also pointed out that according to the different attitudes towards traffic information, travelers can be divided into proactive and short-sighted types, and they have further pointed out that it is precisely because of the differences in attitudes towards traffic information prompts (sometimes these differences even correspond to completely opposite actions taken by travelers) that urban day-to-day travel systems in an information environment can easily evolve into a new rational balance [106]. In the context of intelligent terminals being able to provide personalized information pushes, by fully considering the individual preferences of travelers, Long et al. have customized an update mechanism for traffic information publishing for two typical types of travelers: indifferent and forced. They have found that traffic information publishing that considers the preferences of travelers can enable urban day-to-day travel systems to achieve higher efficiency in UE [112].

4. Development of Macro Traffic Flow Changes in Information Environment

From the review in the last section, it can be inferred that due to the uncertainty of micro individual effects, there are, inevitably, quite a few difficulties and complexities in the analysis of macro traffic flow under the impact of micro factors. Moreover, due to the fact that the distribution of urban macro road traffic flow is a phenomenon formed by the aggregation of micro travel decisions from day-to-day travelers [115], the acquisition of real day-to-day travel data is crucial for research. However, obtaining travel data that can support day-to-day traffic flow allocation models can be very tricky [116], and due to the lack of data, very few studies on day-to-day travel can compare the model results of day-to-day traffic flow allocation with the actual macro state [117]. Therefore, the quality of the macro traffic flow models studied by scholars is often difficult to guarantee, and the difficulties in data validations of proposed models are even more prominent for those situations where macro road networks are disturbed (such as traffic accidents, road closures, etc.).

Nevertheless, despite all the difficulties mentioned above, scholars have still made many efforts to explain macro road traffic flow changes in urban day-to-day travel. They have formed many representative achievements in analyzing the impact of micro travel decisions on macro phenomena, the characteristics of macro traffic flow, and even the effective explanation methods of macro traffic flow in an information environment.

4.1. Traditional Explanations

For the effective explanation of macro traffic flow under the impact of micro travel decisions in urban day-to-day travel systems, traditional explanations have mainly focused on macro traffic flow state, which includes not only the qualitative phenomena but also the state of micro travelers' travel patterns and their appearance in various road segments in the macro road network at different travel times.

4.1.1. Qualitative Macro Phenomena Explanations

The complexity of the macro traffic flow-changing process under the impact of micro decision-making in urban day-to-day travel systems is beyond doubt. Adler et al. have pointed out that in urban travel systems, the route choices of day-to-day travelers are a complex, non-cooperative game process [118]. The macro traffic flow is impacted by many factors. Firstly, the micro factors of travelers: Qi et al. have pointed out that the thinking inertia and route choice preferences of travelers have a great impact on the macro traffic flow allocation, which, in turn, can affect the macro equilibrium state of the urban road network [75]. Secondly, the macro factors of traffic management and control: Hu et al. have pointed out that there is an interaction between certain traffic control measures and network flow changes in the day-to-day travel environment [119], while Chang et al. and Hunt et al. have provided empirical observations of traffic fluctuations in road network disturbances [120,121].

As mentioned above in Section 3.3, in an information environment, diverse ways of collecting travel information have also provided new data acquisition methods for analyzing macro road traffic flow changes in urban day-to-day travel systems. Naveh et al. have formed a dynamic flow change graph of a macro area based on bus SCD and vehicle trajectory data obtained from roadside Bluetooth detectors and have used these dynamic change maps formed by structured data across days and weeks to provide an understanding of urban macro mobility [122]. Sirmatel et al. have proposed a nonlinear moving horizon estimation (NMHE) method based on OD data obtained through information technology and have also constructed a dynamic theoretical basis for macro traffic flow changes based on a macroscopic fundamental diagram (MFD) [123]. Li et al. have proposed a multimodal Logit kernel model based on the combined route data formed by multimodal travel, which represents the macro UE problem in multimodal travel networks as a fixed-point problem and explains the macro allocation of travel route choices [124]. Ma et al. have designed a quantitative model for urban macro traffic performance and have captured the urban traffic performance under micro travel aggregation by introducing a state space model, which can provide a quantitative representation of the degree of macro road traffic congestion [125].

4.1.2. Quantitative Macro Traffic Flow Explanations

The micro behavioral characteristics of travelers make it difficult to discover the patterns of macro traffic flow through continuous time modeling, so using discrete time series analysis methods (daily discrete or weekly discrete) can be more effective [126]. Friesz et al. have used evolutionary game theory to simulate changes in dynamic traffic flow [127]. Cassetta has attempted to describe the probability distribution problem of macro traffic flow states by introducing Markov processes [128]. Cantarella et al. have applied bifurcation theory to confirm that when different model parameters change, different types of traffic flow-changing processes may occur and finally converge to different system steady states [129]. Bie et al. have applied the concept of attraction domain to study the asymptotic steady state of macro traffic flow evolution in day-to-day travel [130]. Li et al. have analyzed the characteristics of travel time volatility (TTV) by introducing algorithms to fit it and have demonstrated that iterative cumulative sum of squares (ICSS) and autoregressive conditional heteroskedasticity family models (ARCHs) are suitable for TTV analysis [131].

Model predictive control (MPC) is one of the widely used algorithms in the adjustment and control analysis of macro traffic flow under the premise of micro road property changes, such as macro traffic flow analysis under the impact of micro ramp flow control or variable speed limits on roads [132–134]. However, some scholars believe that as a nonlinear, non-convex optimization problem, MPC may contain multiple local minima and is usually a non-deterministic polynomial (NP) problem, which is sometimes difficult to solve. Therefore, it was transformed into a mixed-integer linear programming (MILP) problem to obtain a fast solution by introducing proper assumptions [135]. Considering the macro traffic flow analysis under fixed micro travel demand, van den Berg et al. have used the MPC analysis method to discuss the evolution process of traffic flow [136], and as a continuation, van den Berg et al. have also studied the macroscopic traffic flow distribution problem after introducing traffic control measures under time-varying day-to-day travel demand and have used linear piecewise functions and affine functions to simulate the MPC optimization problem and reshaped them into an MILP problem to solve [137].

The above traditional explanations for macro road traffic flow discussed in this section are summarized in Table 5.

Table 5. Research on traditional explanations for macro road traffic flow.

Research Objects	Topic Types	Detailed Research Concerns	Literature
Explanations for macro road traffic flow in urban day-to-day travel	Qualitative Macro phenomena	Complexity of macro phenomena	[118]
		Micro influencing factor: Humans	[119]
		Macro influencing factor: Road flow conditions	[120,121]
		New data acquisition methods for analyzing macro phenomena	[122–125]
	Quantitative Macro Traffic Flow Explanations	Analysis of traffic flow changes caused by micro behavioral characteristics of travelers (often based on discrete time series analysis)	[126–131]
		Analysis of macro traffic flow adjustment and control (often based on model predictive control (MPC) and mixed-integer linear programming (MILP))	[132–137]

4.2. Explanations with Information Factors Considered

Similar to the models mentioned in Section 3.2, the development of explanations for macro traffic flow has also taken information factors into consideration in the early stage, especially those studies on the final equilibrium state of urban day-to-day traffic network flow. This state is surely affected by traffic flow information on travel routes and other information factors like individual travel time cost, network constraints, etc. Although this state may not be quantitatively given to travelers, it is crucial for macro traffic governance in cities and can also be perceived by travelers to some extent, affecting their micro travel decision-making behavior. That is why most studies on macro traffic flow distribution under the impact of micro route choice in day-to-day travel focus on simulating the changing process of macro traffic flow and analyzing the final equilibrium state of network flow.

Actually, finding the UE of a macro traffic network is a multi-criteria system optimization problem; at the same time as the macro network reaches equilibrium, its internal users should also be in an equilibrium state [138]. After the concept of UE in macro networks was proposed [139], for travel systems, Smith and Dafermos used an asymmetric segment cost calculation method to capture UE in road segments as a VI-solving problem [140,141]. To solve the UE problem, as a certain route in a day-to-day travel network is a combination of road segments, the total number of road segments is much smaller than the number of routes; therefore, finding UE in road segments can be easier. Also, a series of studies have utilized sensitivity analysis methods of UE models; these sensitivity analyses can be roughly divided into two categories: directional partial derivative-based methods [142–144] and gradient-based methods [145–148].

As the urban day-to-day travel system is a typical complex system mentioned at the beginning of this section, scholars have not limited their research only to finding the macro UE of urban day-to-day travel systems but have continuously expanded the different types of UE by considering individual differences of micro travelers and different information factors. Hazelton, Nakayama et al. and Sun et al. have studied the stochastic UE (SUE) problem in macro road networks and have explained the concept of SUE by assuming that the perceived travel time of the route is a stochastic variable [46,149,150]. Huang et al. have studied the parameter calibration of SUE and have compared the performance of the multinomial Logit (MNL) model, the length-based conditional Logit (LCL) model, and the congestion-based conditional Logit (CCL) model in SUE model calibration [151]. Site has proposed the concept of state-dependent SUE (SDSUE), which defines the equilibrium state as a fixed point in a Markov assignment process with state-dependent route choice [152]. Guo et al. and Guo have studied the rationality UE (RUE) problem under constrained conditions in macro road networks [153,154]. Torkjazi et al. have proposed the concept of pessimistic UE (PUE) and have compared it with UE. By defining congestion late penalties as additional travel costs, they have discussed the travel flow on typical urban road segments and have pointed out that PUE has a more accurate estimation of flow [155]. In addition, under the background of hybrid operation of autonomous vehicles (AVs) and human-driven vehicles (HVs) in urban day-to-day travel systems, Guo et al., Sun, and Liang et al. have all pointed out that, compared to HVs, AVs have better environmental perception ability and are more receptive to route allocation provided by ITS and, thus, enable the network to achieve better UE [156–158]. Based on this, Guo et al. have proposed the concept of bounded RUE (BRUE) in a mixed scenario of AVs and HVs and have demonstrated that mixed-operation travel systems usually converge to BRUE [156]. The macro traffic flow explanations focusing on UE with different information factors considered are summarized in Table 6.

Table 6. Research on UE of macro traffic networks with different information factors considered.

Detailed Models	Literature	Information Factors Considered				
		Flow on Travel Route	Flow on Travel Road Segments	Individual Travel Time Cost	Road Network Constraints	Past Road Network Status
UE	[77]	√				
	[78]	√		√		
	[82,83]		√	√		
SUE	[35,84,100]	√		√		
	[101]	√	√	√		
SDSUE	[95]		√	√		√
RUE	[79,85]		√	√	√	
PUE	[96]		√	√		
BRUE	[102]	√		√	√	

"√" given in this table means that the corresponding information factor in that column has been considered in the research of the corresponding literature in that row.

4.3. The Impact of Information Environment on Macro Traffic Flow

The macro urban transportation system, represented by the urban road traffic network, is not a direct recipient of traffic information in day-to-day operations but only passively changes in the form of traffic flow through aggregation effects after micro travelers carry out their travel activities. Therefore, there is not much research on the impact of traffic information on macro road traffic flow changes compared to the research on the impact of traffic information on micro travel decision-making.

Relatively early research, due to the lack of widespread use of intelligent terminals, has mostly focused on the guidance information of VMS in cities [159]. Iida et al. have used experimental analysis methods to study travelers' understanding of traffic information quality and its impact on route choice. The results have shown that the quality of traffic information has the same impact on route choice and macro traffic flow [160]. Poulydoropoulou et al. have studied the impact of traffic information before and during travel on micro route choice behavior as well as its impact on macro traffic flow and have pointed out that accurate and timely information is an important factor in guiding travelers to make route choices [161]. Jiang et al. have pointed out that under congested conditions, VMS has a very significant guidance effect on macro traffic flow, but the improvement of road network traffic operation depends on the quality of recommended alternative routes [162].

Later on, scholars focused on the information environment created by intelligent systems like ITS. Klügl et al. have developed a simple model for adaptive route choice simulation, and their simulation results have shown that in the presence of information prompts, as most drivers have to react to the traffic information, the speed at which the macro network reaches an equilibrium state slows down [163]. Cantarella has studied the macro traffic flow evolution mechanism under the influence of ITS by describing the parameter of total user surplus time and has pointed out that the model can be widely applied to the evaluation of ITS on the macro traffic network effect [164]. Roy et al. have established a network physics society coupling framework under the influence of ITS, breaking away from the limitations of most models that only analyze driving behavior and urban macro road traffic network flow. They have attempted to use the mean field game (MFG) limit of non-cooperative games to explain the multi-mode macro traffic operation rules in the information environment [165].

In analyzing the UE of the macro traffic flow-changing process of urban day-to-day travel mentioned in Section 4.2, scholars have found that in an information environment, with the widespread application of ITS, studying the UE state itself is not enough to achieve objective analysis of traffic flow and it is necessary to analyze the mechanism of the traffic flow-changing process that forms UE. He et al. have provided a traffic allocation model in an information environment based on road segment flow variables, proving that the steady-state point of the model corresponds to UE [166]. Based on [166], Guo et al. have extended the model and studied the changes in a macro network affected by micro-level route choices of day-to-day travel based on road segments under continuous and discrete time. They have further pointed out several desirable properties of the proposed model apart from the steady-state point corresponding to UE, including steady-state uniqueness and asymptotic stability [167,168]. Han et al. have tested the model proposed in [166] and some of its properties, like several constant settings and the equilibrium state under their constraints [169]. Guo et al. have proposed a universal route-based day-to-day travel model that equates the observation of the road traffic flow-changing process to a minimization problem [168]. Smith et al. have also proposed a dynamic system model for day-to-day travel based on route adjustment using the decomposition of traveler flow in road segment transition nodes as the modeling basis [170], but same as in [168], the route overlap problem mentioned in [166] has not been considered. Zhu et al. have investigated the flexibility of generalized Bayesian models in capturing UE and have demonstrated that the route choice dynamics generated by Bayesian models based on infinite memory and mean variance perceptual knowledge must converge to UE, and even adding bounded weights to perceptual knowledge will not affect the model convergence [171].

5. Development of Information Environment Understanding

With the constant development of various intelligent systems and terminals that create urban day-to-day travel systems, scholars also tend to have a deeper understanding of the information environment. The types of traffic information provided to urban day-to-day travelers in an information environment can be further divided into global and local traffic information according to the range of travelers obtained. Global traffic information, as it is called, can be obtained through various public information dissemination channels, such as road flow status, traffic control strategies, etc., whereas local traffic information is released through certain channels and only available to some travelers, such as sudden congestion and control information, on certain parts of the urban road network. The impacts of different types of traffic information on micro travel decision-making are different, and, in turn, their impacts on the distribution of macro traffic flow also vary.

5.1. The Impact of Global Traffic Information on Day-to-Day Travelers

The most common type of information that urban day-to-day travelers can access in an information environment is travel-related information that can be obtained through various public information dissemination channels. In this section, it is defined as global traffic information. In the old era, when smartphones and intelligent terminals were not yet fully popularized, the scope of global traffic information was relatively narrow. At that time, specific urban traffic governance strategies known to day-to-day travelers, such as road congestion pricing, were types of important global information that affected their travel strategies.

Many scholars have also conducted research on the impact of this specific global traffic information on micro travel decision-making and macro road traffic flow. Yang et al. have pointed out that congestion pricing can enable travelers to internalize this external impact and to form their own corresponding travel strategies, and the macro road traffic flow can also achieve a steady state as a result [172]. Henderson, Carey et al., Yang et al., and Wie have also conducted similar studies on the impact of congestion pricing information on individuals and have pointed out that congestion pricing strategies can induce more effective spatiotemporal utilization of the road network by travelers. Moreover, congestion information affects individuals, and individuals affect the whole, which, in turn, can lead the entire urban road network to change from one steady state to another [173–176]. Sandholm has found that day-to-day travelers can use the dynamic evolution of road networks caused by congestion pricing information to adjust more reasonable route choice behavior [177]. Friesz et al. and Yang et al. have conducted a study on the dynamic evolution of road network traffic brought about by congestion pricing policy information [178,179] and have found that in the optimization process of day-to-day traffic flow systems, the dynamic marginal congestion price can lead to faster system convergence than the fixed [179]. Tan et al. have studied the persistent effect of congestion pricing and have introduced the differences in day-to-day route choice adjustment behavior of travelers and the travel cost factors in time and money. In their study, different users are grouped, the equilibrium state and its properties of the system are examined, and the Pareto optimal (minimum time and money costs) state of the system is found [180]. Irfan et al. have developed a polynomial Logit model based on SP to estimate the perception of travelers towards the expected utility, and have analyzed the significant impact of congestion pricing on reducing demand for car-based travel [181].

Later, research on global traffic information was no longer limited to a single type of traffic governance strategy. Various types of ATISs that can be accessed by travelers have included information such as real-time road flow and congestion status in the research scope. Zhang et al. have proposed an optimized publishing strategy for post-travel time information provided to travelers, which provides travelers with information that may not be entirely accurate but is within a trustworthy range. In their research, the problem of day-to-day travel systems in achieving UE has been described as a dynamic programming problem so that the best information publishing strategy can be found [182]. Liu et al. have discussed the effective information publishing strategy in the return to work (RTW) stage and have quantified the impact of information publishing on different types of travel demand. They found the phenomenon that private car travel demand recovered faster than public transportation travel demand when the urban transport system was fully opened to the public after the COVID-19 pandemic [183].

5.2. The Impact of Local Traffic Information on Day-to-Day Travelers

The complexity of urban day-to-day travel systems in an information environment determines that all participants in the system may not be able to access the same travel reference information at all times. This phenomenon has a local impact on urban day-to-day travel. It may be caused by local failures of the urban travel system (such as sudden road accidents, local operational failures of the public transportation system, etc.) or by the formation of travel groups among several travelers and collective travel decisions. Scholars have noticed such issues and have already conducted a series of related studies.

In response to the situation where only local travelers can acquire certain traffic information due to local failure of the urban travel system, He et al. have carefully studied the changes in the route choice behavior of travelers after a specific bridge collapse. They have found that the vast majority of traffic allocation models are not suitable for situations where road functions are interrupted, and the past experiences of travelers lose their efficiency. They have also pointed out that unexpected network changes will greatly disturb the distribution of macro traffic flow [184]. Marra et al. have analyzed the impact of local emergencies in urban road networks on travelers and have defined these types of emergencies that may generate local information indicating disturbances and delays. They have also made a similar conclusion as in [184], that is, most travelers still rely on their past travel experiences, which have lost efficiency in making route choices when encountering local emergencies [185]. Barroso et al. have broadly pointed out the difficulties that local road congestion caused by traffic accidents, temporary commercial activities, and other factors in cities cause for day-to-day travelers and have pointed out that travelers who obtain such local traffic information still tend to rely more on their experiences and habits to make travel decisions [186].

In response to the situation where certain travelers have formed travel groups, made collective travel decisions, and had a local impact on urban day-to-day travel systems, Tang noticed the positive effects of group learning among day-to-day travelers and pointed out that within a certain range, exchanging travel experiences among travelers can improve the overall urban travel situation, but beyond a certain range, the side effects will become greater [187]. Yang et al. and Qi et al. have pointed out that there is a strong behavioral correlation between those urban day-to-day travelers who behave according to the representative resident activity pattern (RAP), as their travel decisions are driven by the same activity characteristics. They have even proposed a RAP recognition method in the hope of better explaining the activity patterns of the clusters of urban day-to-day travelers [188,189]. Zhao et al. have analyzed the spatiotemporal correlation between passengers in public transportation data and have also pointed out that there is a correlation between the mobility of passengers with similar ODs, which can have an impact on the quality of urban public transportation services [190]. Zeng et al. have specifically focused on the local impacts of organized collective route planning behavior on urban day-to-day travel systems, represented by different vehicle groups such as ambulances operated by certain stakeholders [191].

The review of the development of the understanding of different types of traffic information in an information environment in this section is summarized in Table 7.

Table 7. Two different types of traffic information that can be obtained.

Information Types	Specific Information	Literature
Global traffic information	Congestion pricing information	[172–181]
	Travel time cost information	[182]
	Guide information after pandemic	[183]
Local traffic information	Local emergencies in urban road network	[184,185]
	Local congestion caused by temporary traffic accidents or commercial activities	[186]
	Shared travel strategy between travelers	[187–190]
	Inertial information from certain vehicle operation organizations	[191]

6. Open Issues

Through the discussion in Section 2 to Section 5, it can be found that with the advent of the information age, traditional urban day-to-day travel systems have been deeply influenced by traffic information. Due to the complexity of the urban day-to-day travel system itself, the introduction of traffic information makes the micro decisions and macro changes of the system even more complex. Currently, there is no complete theoretical system to explain the day-to-day travel issues in an information environment, but scholars have always been exploring it. Therefore, there are some open issues and interesting research directions that are worth discussion in this section.

6.1. Using Increasingly Diverse Information Technology Methods for Day-to-Day Travel

The continuous penetration of information technology has made it increasingly difficult to understand the development and changes taking place in urban day-to-day travel systems. In this context, effective governance of urban travel systems should take the initiative to embrace information. The penetration of information technology into urban day-to-day travel systems should be seen as a "double-edged sword". While information technology is increasing the complexity of the system, it also provides new opportunities for using new data acquisition and analysis methodologies in the information age to solve difficult problems in urban traffic governance.

For example, considering the high popularity of smartphones nowadays, with travelers participating in day-to-day travel systems, mobile communication operators can obtain natural desensitized travel data—mobile signaling data (MSD)—in their backend more conveniently than through traditional travel surveys [192]. Although not very precise, MSD can at least reflect the changes in the location and movement process of smartphone users (namely, the travelers) under sectors of base stations. Combined with the corresponding urban functional areas (such as business areas, residential areas, entertainment areas, etc.) served by specific base stations, it is possible to fit the traffic communities and travel circles of most urban day-to-day travelers. Due to limited data accuracy, such fitting may have certain errors, but compared to traditional travel survey methods, its data utilization efficiency is higher, and the fitted travel circle also has higher credibility.

Some efforts have already been made by scholars in this direction. Barmpounakis et al. and Vial et al. have attempted to use MSD, combined with urban vehicles that can be used as wireless perception nodes, to extract the location, movement, and travel characteristics of urban travelers using specific transportation tools such as electric two-wheelers and bicycles [193,194]. Yao et al. have tried to use MSD combined with global positioning system (GPS) data to identify day-to-day ODs of travelers as well as their travel behavior similarities [195]. Guo et al. have proposed an activity-based model (ABM) with skeleton scheduling constraints to address the issue of MSD lacking individual socio-economic attributes. In addition to perceiving specific travel activities, the model also considers the attributes of activity locations, achieving more accurate identification of activity objectives [196]. Huang et al. have also proposed an accurate map-matching method tailored for MSD based on the incremental hidden Markov model (HMM) algorithm. The proposed algorithm has solved the problems of drift data, ping-pong sequences, and spatiotemporal sparsity in MSD and, thus, can properly match large-scale real-time maps with day-to-day travels [197].

There is reason to believe that with the increase in the dimensions of day-to-day travel data resources available in the information age and the advancement of methodologies for processing massive amounts of data, scholars will also propose more competitive methodologies to explore those issues related to the laws of urban day-to-day travel systems that cannot be solved by traditional travel surveys.

6.2. Deep Integration of Micro Travel Decision-Making and Macro Traffic Analysis

From the relevant research on modeling urban day-to-day travel and the impact of the information environment on it in the previous sections, it can be found that there are two clear main lines in the relevant research. The first one is to discuss the travel decision-making of micro travelers, and the second one is to discuss the macro aggregation effects of day-to-day travel. However, as urban day-to-day travel systems can be recognized as complex systems, their macro and micro analyses should not be completely separated. Scholars have also discovered this issue and have attempted to pursue a deep integration of micro travel decision-making and macro traffic analysis.

Some scholars have attempted to start their research from the micro level of travel decision-making and then expand it to the macro level. Xu et al. have focused on the presence of local interruptions in urban road networks. Based on the subjective perception of micro travelers and quantitative average excess travel time, they have captured the uncertainty of target travel time and have extended it to macro UE analysis after interruption adjustment [198]. Li et al. have attempted to establish a heterogeneous intelligent agent model by first establishing the learning rules for different agents, then demonstrating the ultimate macro asymptotic stability of day-to-day travel systems and finally, incorporating some previous network models of day-to-day travel into their theoretical framework [199]. Meneguzzer has focused on defining and designing individual travel inertia, memory differences, and travel costs in an established nonlinear dynamical system and has studied the impact of those micro parameters on the stability of the macro network during its operation [200]. Zhu et al. have developed a data-driven framework for dynamically modeling day-to-day route choice and have ultimately extended the model objectives to changes in the operation status of day-to-day travel systems [201]. The model proposed by Guarda et al. not only learned the OD matrix and travel utility function for specific time periods but also learned the network flow parameters, achieving the fusion of the model from micro to macro when analyzing network UE [202].

In addition, some scholars have attempted to start their research by analyzing and discussing macro phenomena and then penetrating into the micro level. Zhang et al. have mainly studied MFD modeling of travel network operation and have ultimately focused on optimizing micro travel routes and time selection [203]. Kazhaniakin et al. have established an ecological transportation service decision-making system, which ultimately promotes green travel behavior among travelers through online macro game changes of the system [204]. Zhang et al. started from the macro perspective of transportation demand management (TDM) and then transformed TDM into classical state space analysis using the theory of supply-demand interaction and finally, analyzed the micro route travel cost under TDM by introducing a state-dependent regional practice formation function [205]. Zhang et al. have used clustering algorithms to analyze the non-objectivity of micro travel under the premise of macro traffic flow distribution [206]. Subsequently, Xiao et al. have proposed the basic behavior pattern of "arrive-stay-leave (ASL)" for individuals based on urban regional travel heat maps and have interpreted the heat map from a macro perspective using multi-head attention networks. Finally, the multi-scale differences of micro ASL have been understood through 3D spatiotemporal convolutional networks [207].

From the previous discussion, it can be seen that although macro and micro integrated modeling of day-to-day travel systems has been implemented, scholars have only made some attempts, but it is still not systematic. To be specific, the mainstream of urban day-to-day travel systems is still in three main topics: (1) micro travel decisions and their influencing factors, (2) macro traffic flow change analysis, and (3) the analysis of the advantages and disadvantages of an information environment for travel systems. The analysis of urban day-to-day travel systems in an information environment urgently requires the support of emerging theories, breaking the current situation where research studies in the three main topics are all on their own. And it can be expected that the deep integration of micro travel decision-making and macro traffic analysis would be the focus of urban day-to-day travel-related research.

6.3. Developing Novel Theories to Explain Urban Day-to-Day Travel Systems

As mentioned earlier, urban day-to-day travel systems are typical complex systems that have the characteristics of any complex system, such as: (1) feedback, which means travel memory will provide travelers with different degrees of positive and negative feedback and make travelers respond to the feedback in subsequent trips; (2) instability, which means it cannot be assumed that the previously observed system state will remain unchanged in the future; (3) interactivity among participants, which means there is a competitive relationship among travelers in choosing a reasonable route as much as possible and reducing travel time costs; (4) adaptability, which means that travelers have the ability to adjust their own travel decision-making under the driving force of changes in the travel system on their travel effects; (5) openness, which means that the transportation system and travel participants are constantly changing, and there is a coupling effect between travelers and the environment, making it difficult to distinguish between external and endogenous effects that affect system changes. In future research, it is entirely possible to attempt macro and micro integrated modeling of day-to-day travel systems from the perspective of complex system dynamics. Some of the literature that has been reviewed earlier in this paper, such as [75,106,109,171,199], has already reflected the thinking of complex system dynamics.

Another theoretical system worth exploring is the quantum mechanics thinking of individual travelers, as Vitetta has already mentioned that the micro travel route choice behavior and the macro travel effect can be described by a quantum utility model [208]. Moreover, Lipovetsky has also pointed out that discrete decision-making can be described as a quantum paradigm [209]. Actually, in day-to-day travel phenomena, there are many dynamic characteristics similar to particle motion in physics. When grasping the dynamic characteristics of complex systems, it is often difficult to explain the motion state of micro particles, but the macro characteristics of the system are often presented in a certain form. Day-to-day travelers precisely possess the micro characteristics of moving particles in physics, but their aggregation behavior can also exhibit macro fluctuations. Unfortunately, until now, although quantum mechanics thinking has been considered to be applied in travel systems, it is often applied in enhancing computational performance by employing quantum computing in processing travel big data [210,211] rather than introducing the concept of quantum mechanics into the explanation of urban day-to-day travel systems. However, it is exciting that sporadic scholars like Zhao et al. have already begun to attempt to describe urban day-to-day travel decision-making by employing quantum decision models [212]. Their description is not limited to the micro level but can also analyze the feedback effect of travel safety and the time costs on individual travelers from the macro level, and the theoretical advantages of applying quantum mechanics to urban day-to-day travel systems are demonstrated. In fact, using the uncertainty relationship between particle motion and system steady states to explain the uncertainty in travel and the uncertainty relationship between travelers and the possible state of the urban day-to-day travel system will be very interesting and worth looking forward to.

7. Conclusions

Urban day-to-day travel systems are complex systems with almost all of the complex system characteristics. After introducing traffic information, with the diversification of information exchange channels between travelers and macro road networks, the complexity of urban day-to-day travel systems is further increased. Understanding the complex urban day-to-day travel system is of great significance for the sustainable development of cities in terms of traffic governance. This paper first reviews the traditional micro decision-making of urban day-to-day travel and the macro road traffic flow analysis as the aggregation effect of micro travel decisions, clarifying some representative methodologies commonly used in these specific research problems. Subsequently, this paper clarifies that in the information era, the ways of obtaining traffic information have become increasingly diverse, and the introduction of traffic information can bring profound changes to urban day-to-day travel systems. After commenting on this, a dialectical discussion has been conducted on the potential impact of traffic information on micro travel decisions and macro traffic flow changes in urban day-to-day travel systems. Finally, some open issues regarding the future theoretical development direction of urban day-to-day travel systems in an information environment have been given, hoping to arouse higher research interest among scholars in this field.

Due to the lack of systematic discussion in previous review papers on the methodologies of explaining urban day-to-day travel systems, let alone systematic discussion of urban day-to-day travel systems in an information environment, the main contribution of this paper is just a systematic review of the traditional theoretical development of urban day-to-day travel systems, as well as the innovative theoretical development of urban day-to-day travel systems in an information environment after introducing traffic information. In addition, this paper has also pointed out several challenging open issues for the future theoretical development of urban day-to-day travel systems. Of course, considering the ubiquitous and rapid development of ICT in the current lives of urban residents, the relevant research reviewed in this paper only extends to the widespread use of smartphones and smart terminals among travelers and the information environment created by the coexistence of traditional travel information acquisition media, various ITS-related applications, and online social media. With the further development of ICT, there will be new and unpredictable changes in the travel decisions of urban day-to-day travelers and even the future development of urban day-to-day travel systems.

In addition, in the discussion of this paper, relevant, innovative work being carried out on urban day-to-day travel systems in an information environment has also been pointed out. Firstly, scholars have found that instead of passively viewing traffic information as a factor that increases the complexity of urban day-to-day travel systems, it is better to actively view it as a tool for fitting higher fidelity OD pairs and judging travel modes between them. Secondly, scholars have found that discussing micro-level travel decisions and macro-level traffic flow changes separately is increasingly insufficient to objectively explain the development of and changes in urban day-to-day travel in an information environment; deep integration of the research on both macro and micro levels is underway. Moreover, scholars are striving to explore new theories that can provide more effective explanations for urban day-to-day travel systems in an information environment; emerging theories such as complex system dynamics and quantum mechanics are the most representative and promising ones.

Through the review of this paper, some beneficial insights can be given to the management and governance departments of contemporary urban travel systems: firstly, the governance of urban travel systems in an information environment should be one of the core tasks of long-term urban sustainable development; secondly, if information technology can be fully utilized to solve the source problem of traffic survey data, the "knowledge" contained in day-to-day travel data can be fully explored through various emerging algorithms in the information age; finally, for day-to-day travel systems in an information environment, from the classification of personality differences in the micro travel decision-making process of individual travelers to the long-term and short-term analysis of macro road traffic flow-changing processes under the influence of micro travel decisions, and even to the establishment of a macro and micro integrated theoretical analysis system, these are all needed to break away from the traditional single discipline of transportation engineering in seeking proper theoretical explanations and establishing new theoretical systems.

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