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Sustainable Traffic Management for Smart Cities Using Internet-of-Things-Oriented Intelligent Transportation Systems (ITS): Challenges and Recommendations

Auwal Alhassan Musa [1], Salim Idris Malami [2], Fayez Alanazi [3,*], Wassef Ounaies [3], Mohammed Alshammari [3] and Sadi Ibrahim Haruna [4]

1. Civil Engineering Department, Mewar University, Chittorgarh 312901, India; auwalalhassanmusa@gmail.com
2. School of Energy, Geo-Science, Infrastructure and Society, Institute for Sustainable Built Environment, Heriot-Watt University, Edinburgh EH14 4AS, UK; salimmalami@gmail.com
3. Civil Engineering Department, College of Engineering, Jouf University, Sakaka 72388, Saudi Arabia; wounaies@ju.edu.sa (W.O.); 391101247@ju.edu.sa (M.A.)
4. School of Civil Engineering, Tianjin University, Tianjin 300350, China; siharuna.civ@buk.edu.ng

* Correspondence: fkalanazi@ju.edu.sa

Abstract: The emergence of smart cities has addressed many critical challenges associated with conventional urbanization worldwide. However, sustainable traffic management in smart cities has received less attention from researchers due to its complex and heterogeneous nature, which directly affects smart cities' transportation systems. The study aimed at addressing traffic-related issues in smart cities by focusing on establishing a sustainable framework based on the Internet of Things (IoT) and Intelligent Transportation System (ITS) applications. To sustain the management of traffic in smart cities, which is composed of a hybridized stream of human-driven vehicles (HDV) and connected automated vehicles (CAV), a dual approach was employed by considering traffic as either modeling- and analysis-based, or/and the decision-making issues of previous research works. Moreover, the two techniques utilized real-time traffic data, and collected vehicle and road users' information using AI sensors and ITS-based devices. These data can be processed and transmitted using machine learning algorithms and cloud computing for traffic management, traffic decision-making policies, and documentation for future use. The proposed framework suggests that deploying such systems in smart cities' transportation could play a significant role in predicting traffic outcomes, traffic forecasting, traffic decongestion, minimizing road users' lost hours, suggesting alternative routes, and simplifying urban transportation activities for urban dwellers. Also, the proposed integrated framework adopted can address issues related to pollution in smart cities by promoting public transportation and advocating low-carbon emission zones. By implementing these solutions, smart cities can achieve sustainable traffic management and reduce their carbon footprint, making them livable and environmentally friendly.

Keywords: artificial intelligence; Internet of Things; smart cities; Intelligent Transportation System

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Citation: Musa, A.A.; Malami, S.I.; Alanazi, F.; Ounaies, W.; Alshammari, M.; Haruna, S.I. Sustainable Traffic Management for Smart Cities Using Internet-of-Things-Oriented Intelligent Transportation Systems (ITS): Challenges and Recommendations. *Sustainability* **2023**, *15*, 9859. https://doi.org/10.3390/su15139859

Academic Editors: Maxim A. Dulebenets, Keshuang Tang, Hong Zhu and Ashish Bhaskar

Received: 13 April 2023
Revised: 17 June 2023
Accepted: 19 June 2023
Published: 21 June 2023

1. Introduction

1.1. Background of the Study

A smart city is a physically occupied entity that integrates tangible and non-tangible resources for utilization by its inhabitants. The compatibility of ICT-based infrastructures with built-in infrastructures is necessary to become a system capable of delivering expected services to inhabitants, without affecting or compromising the quality of life [1]. It is also regarded as an innovation designed to offer sustainable growth and service by fulfilling the six dimensions of sustainability: economy, people, governance, mobility, environment, and living [2]. As a critical element and one of the six dimensions for developing smart cities, mobility should be given special and considerable attention. The idea of sustainable transportation systems as an integral part of developing smart cities is being defeated. Because the conventional systems of transportation adopted in traditional cities are coupled with in-built challenges such as accident occurrence, congestion problems, pollution, etc., these are menaces to the system and hinder the socio-economic activities of smart cities [3].

As part of the objectives stated by the United Nations [4], which require a broader and more careful investment in advocating sustainability goals, the idea of establishing smart/sustainable cities was introduced to serve as one of the long-term mitigation measures of overcrowding in most developed cities due to the unprecedented and uncontrollable rise in urban migrations, as well as to serve as an attempt to relieve the burden of densified activities resulting from traffic [5]. Moreover, the population of urban centers is expected to increase as much as 63% by the year 2050 [6]. Also, a report from the World Bank, which considers data from the last decade only, shows that urban migrations in most urban centers have incrementally increased [7], as presented in Table 1. However, there is no tangible and sustainable provision for accommodating such a continuously growing phenomenon; this makes the development of smart cities serve as an emergent means of decongesting overcrowded cities worldwide. Therefore, smart cities' rapid and continuous growth worldwide, especially in developed countries, has brought about tremendous improvements in various sectors, such as energy management, waste management, and public safety and security [8].

Table 1. Percentage of urban population compared to the total population within one decade [7].

Country	Population	
	2010	**2020**
Australia	67.45	85.90
Turkey	70.48	75.60
England	79.50	83.70
Germany	73.81	76.40
Holland	82.74	92.50
Japan	90.54	91.40
Sweden	85.05	87.70
Norway	79.10	83.40

As a crucial sector and one of the backbones for the development of smart cities, transportation needs to receive considerable attention through achieving optimum mobility by managing traffic congestion, attaining safety by minimizing accidents, and mitigating air pollution by reducing exhaust emissions from vehicles, while improving socio-economic objectives. However, the sustainable management of traffic in smart cities has received less attention from researchers, despite its complex and heterogeneous nature, which has direct impacts on the transportation systems of smart cities [9]. According to a report by the World Health Organization (WHO), more than 1.3 million deaths are caused by road accidents annually, and over 90% of these deaths occur in low- and middle-income countries [10]. In addition to the loss of human lives, traffic congestion and accidents have a significant economic impact, resulting in the loss of productivity and increase in healthcare costs [10]. As one of the most built-in challenging factors to transportation, traffic congestion will keep rising proportionally with cities' development, which directly affects their socio-economic activities [11]. Most economic and social activities rely on integrated and sustainable transportation, and as the cities are growing due to other activities, transportation systems should be expanded to cover and accommodate expected developments. Integrating transportation management with advanced technology will also help tremendously in attaining the objectives of smart cities [12].

Traffic congestion has been identified as a significant global challenge of urban areas. The problem is particularly acute in smart cities, where the population is overgrowing, and the number of vehicles on the roads is increasing. World cities are facing challenges of having a heterogonous traffic flow with the exponential rise in traffic which surpasses the capacity of the roads. These have necessitated regulating and managing vehicles to have an adequate traffic flow. However, traffic congestion is inevitable, but can be minimized to the barest level, and for a smart city to become livable, it is necessary to couple the general activities with smoother and sustainable transportation systems; these systems can be supported by cooperating with Intelligent Transportation Systems [13].

The idea of decongesting cities through traffic regulations is based on minimizing the direct and indirect impacts of traffic congestion [14]. These direct impacts include road accidents, exhausts polluting the environment, fuel waste, etc., while indirect effects are related to travel time loss [15]. Decongesting roads and obtaining cleaner transportation systems are the basis of sustainable transportation; decongestion by imposing traffic regulations through the implementation of advanced technology helps reduce the number of road accidents and promotes a better accessible environment with a lower threat of degradation and pollution [16]. A rapidly and significantly increasing urban population is the main force causing air pollution due to traffic emissions; records indicated that more than 50% of fuels produced globally are consumed by transportation industries which contribute significantly to polluting the environment, and this percentage will increase in the years to come due to the unprecedented continuous vehicle ownership across the world [17]. Both non-current (which normally results from traffic signal faults and malfunctioning, accidents, sudden damages to roads infrastructures such as bridges failures, etc.) and recurrent traffic congestions (which result from consistent and higher volumes of traffic at certain hours within particular sections of a road) contribute to polluting the environment through the release of harmful gaseous substances such as carbon dioxide, carbon monoxide, volatile organic compound, nitrogen oxide, particulate matters, etc., by vehicles, which could lead to a defeat of the aims of sustainable transportation if not addressed [18,19].

Therefore, paradigm shifts in driving and obtaining harmonized and holistic approaches for proper decision-making in transportation are needed. These result from the need to optimally address traffic issues and find ways to improve them. The aim of this study is to address traffic-related issues in smart cities by focusing on establishing a sustainable framework based on the application of the Internet of Things (IoT) and Intelligent Transportation System (ITS). Also, the gap between trending advanced technologies and smart city traffic management has been explored. This study can equally serve as a guide in developing the framework for proper traffic management in smart cities according to the generic employability of Internet of Things (IoT)-based Intelligent Transportation System (ITS) for sustainable traffic management in smart cities, as presented in Figure 1.

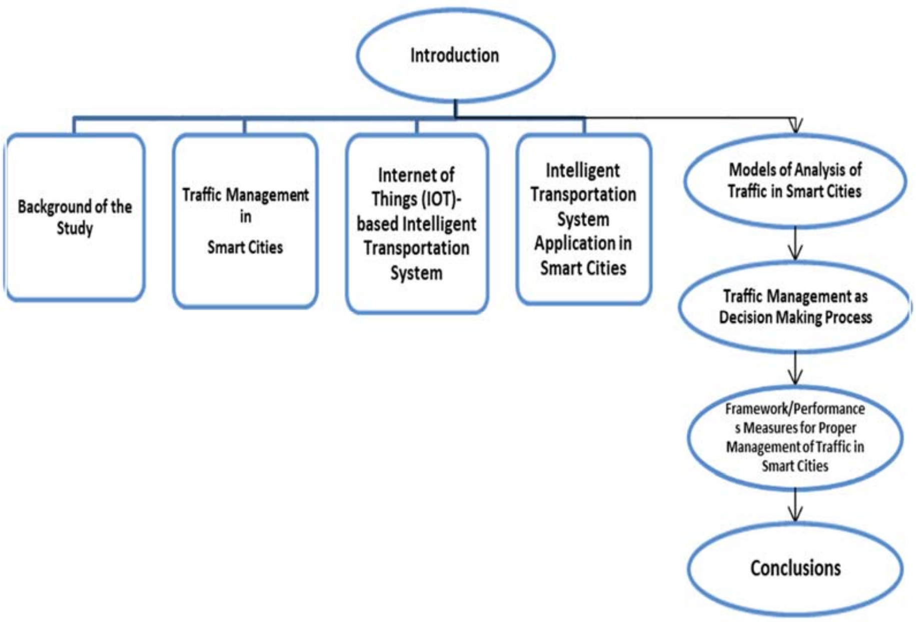

Figure 1. Sequential workflow of the research.

1.2. Traffic Management in Smart Cities

Traffic congestion is a social and environmental nuisance that directly and indirectly impacts a country's economy [20]. Research conducted by [21] shows that on an average basis in United States of America, people lose 338 h annually in traffic; this is a replica of scenarios in most urban centers across the world, as the demand for increasing traffic has exceeded the existing available roads, leading to complexity in managing the traffic. In an attempt to avoid the occurrence of such a phenomenon while developing smart cities, it is necessary to establish rigorous and robust transportation predictive approaches and decision-making tools compatible with the expected nature of the traffic [22].

Conventionally, first and modern traffic signals were initially introduced in New York City in the year 1918, which were managed manually through a centralized control room [23]. The system was based on fixed signal timing. Further improvements and advancements were made in 1982, which led to the invention of the current conventional three-colored traffic light model with an adaptive light, which works based on real-time traffic [24]. Due to its flexibility and versatility in managing traffic, it has become widely accepted in many urban centers worldwide. However, the system could not adopt dynamisms [25]. Another precedent development was invented, which considers the dynamism of traffic to replace the older version of traffic control schemes.

The high rise in the population and other activities tend to render all these conventional traffic signals less effective. Hence, upgrading these obsolete systems to the current conditions involves coupling traffic management with the advanced technology of AI. The work of [26] was among the prominent works which focused on providing robust detection-automated platforms for managing traffic. The system works using real-time traffic data, including the speed and volume of vehicles, which is fed into a server powered with IoT-configured devices to perform various computations and present signals at a time in accordance with the lane capacities and volume of traffic. This has helped in automating the traffic in a seamless process. However, these techniques are integrated with sensitive and expensive devices such as video image processing, microwave radar, laser radar, passive infrared, ultrasonic, and passive acoustic array, of which the maintenance might be difficult, and they might be affected by adverse weather and other environmental nuisances. However, many approaches, mainly automated in managing urban traffic, are evolving with improved features. Another work that embodied hardware and software intelligence was developed by [23] to suit heavy and heterogeneous traffic conditions by using embedded PCs in dynamic traffic light control through WebIOPI REST API in smart cities. The system was tested in the city of Makkah, Saudi Arabia.

1.3. Internet of Things (IoT)-Based Intelligent Transportation System

The Intelligent Transportation Systems (ITS) was initially developed to help cities in attaining issues related to road traffic. However, due to its versatility, the system has been broadening to cover autonomous tolls fare collection, freight and fleeting system management, application of GIS, innovative satellite technologies, etc., especially in organized cities. Artificial intelligence is a driving factor for the management of transportation in smart cities. Its deployment will help in seamless vehicular movement, traffic detection, accident avoidance, obtaining real-time information of vehicles and other road users, enhancing security, adding efficiency to the system by converting it to be human-error-free, and providing prompt safety and support to the drivers. The objective of the already unveiled idea of sustainable traffic management using the ITS approach in smart cities is to establish robust transportation systems that could provide reliable and efficient networks, manage the overall travel time, minimize fuel consumption, and mitigate expected pollution-threatened environments. This can be achieved through consistent and reliable collection, organization, and analysis of data by presenting the result for proper and timely traffic decision-making processes, and these innovative ways have to be compatible with the versatile features of smart cities [27].

1.4. Applications of the Intelligent Transportation System in Smart Cities

1.4.1. Detecting Transportation Incidences

Entire transportation systems are vulnerable to the occurrence of unavoidable incidences due to human–machine interactions. ITS can be deployed as an aiding tool in detecting such incidences. The real-time data and location can be sent to/or communicated with the control center for effective management. These incidences can be accidents, traffic congestion, or a security threat. The detected information can be used to give road commuters an alternative route. To ascertain this detection capability of ITS, a relatively same concept was employed by Gothenburg's tram system in Sweden [28], which indicates that these incidence detection devices and sensors have contributed immensely to energy saving, re-routing, and the management of traffic from the incidences. Therefore, adopting this in smart cities will serve as reliable tools for managing traffic [29].

1.4.2. Automated Ramp Control System

Most activities in smart cities are organized to be automated, and as part of an ITS-based IoT means of managing traffic, which works with sensing devices, the sensors will detect the traffic density, speed, and volume of a particular section of the road. The data fed through sensing the optimal level and spaces between the streams of traffic will be analyzed, and the output of the results will promptly decide on the volume and speed limit that will be expected based on the stream of the traffic through the usage ramping control [30].

1.4.3. Traffic Signal Management

As presented earlier, most ITS devices are detectors, and balancing the traffic supply and capacity of the road network is a challenging task that cannot be easily controlled manually. However, with ITS-based inductive detectors installed on the road's surface, traffic volume, speed, and queue can be detected and give automatic solutions through communication with the central server of the main control room [31]. The baseline working condition is that the communication devices should be versatile and have full network coverage and processing capabilities to ensure timely data processing. This is where the full implementation of IoT-based devices comes into playing a vital role in the management of traffic; these devices with powerful processors were normally configured to give adequate cycle time and green times for each of the signals, and these detectors were designed to ensure that priority vehicles are given special consideration. The detection is usually conducted by integrating GPS devices in the systems linked with the central control rooms in the cities. These devices were in commercial usage, and they were introduced by the Sydney Coordinated Adaptive Traffic System and Split (SCATS), Cycle Time and Offset, Optimization Technique (SCOOT); these systems were practically deployed in Kingston, a suburb in London, UK, as a gating system [32].

1.4.4. Effective Parking Management Tools in Smart Cities

In smart cities, parking provisions and locations are crucial because non-proper and inappropriate parking may render some traffic management systems dysfunctional. However, parking in smart cities may be partially based on ITS. However, incorporating ITS into conventional parking methods will help commuters with information on parking guidance, payment methods, locations reserved as on-street parking lots, and space management [33]. An ITS parking payment was extensively employed in most cities of Europe, especially in Spain.

1.4.5. Demand-Responsive Transport Management (DRTM)

One of the areas in which ITS-based IoT will play an immense role in smart cities is Demand-Responsive Transport Management (DRTM). Conventionally, most public transport vehicles were designed to operate on specific routes, irrespective of the variability of traffic changes. To let passengers get real-time and exact routes, alternative routes, expected times of trips, and the number of commuters in particular vehicles, flexible scheduling, and booking systems is usually overlapped with the public transport systems [32].

1.4.6. Logistics Management

The characteristics of smart cities, and inter-city transportation of goods and services remain one of the backbones for socio-economic development, and smart cities are no exception in this regard. Fleet and freight management is of paramount importance to companies, and this includes an ability to track vehicles, predict routes, origins and destinations, trips schedules, alternative route detections, and the management of fuel consumption executed using satellite and radio technology. Due to the limitations and broad width of these technologies, they can be deployed within specific geographic locations, of which a smart city is a typical and precise example. In the research conducted, it was found that the implementation of these technologies to the logistic sector will help companies save up to 9% of the total running cost [33].

1.4.7. Special Provision to Vulnerable Road Commuters

To have considerations and maintain the equity for all classes of people in smart cities, people vulnerable to the threat of accidents need special treatment regarding their usage of transportation infrastructures, which conventional traffic management gives less attention to due to poor perceptions of road events. An IoT-based ITS can be used due to its sensitive nature to provide a system helping specific groups of people with limited capabilities on the road. These solutions can be used in pedestrian crossing areas and other public locations [34].

1.4.8. Route Guidance

As a segment of ITS, GPS is used for obtaining route information linked to origin and destination, and the system could be used to reduce energy consumption and travel time management. It will also help drivers find an alternative route in which real-time information gives congestion data of the particular route [30,35,36].

1.4.9. Cooperative Perception

The development of smart cities keeps growing with an unprecedented increasing ownership of automated vehicles, aiming to encourage sustainability by reducing fuel consumption and decreasing pollution, while providing more comfort to the vehicle users, helping attain the safety of the entire transportation system [37]. These vehicles should have a clear perception of the surrounding environment, usually achieved through installing sensors, cameras, radars, lidars, etc. [38]. However, these conventional devices and systems have built-in deficiencies of not working to the probable expectations, especially under extreme weather conditions [39]. To overcome these limitations of conventional systems and devices, a cooperative perception was developed, which works with the help of wireless communications between devices and systems, then transmits and transfers information between the vehicles and infrastructure nodes [40], and it served as an avenue for the timely detection of the surrounding environment and other temporary obstacles, especially unconnected infrastructure, impacting the roads [41].

To bridge the gap of blind spots in real-time maps, which are mainly caused by obstacles, improved systems of cooperative perception employed the application of GNSS/INS (Global Navigation Satellite System and Inertial Navigation System) [42]. However, these tools have been in use for decades as navigational tools. Nevertheless, data fusion happens to be the major challenge for these integrated systems, usually addressed using the Kalman filter. Apart from the conventional Kalman filter, various improved Kalman filters have been developed to cover the faults of the conventional Kalman filter in the ability to detect only linear systems in the navigation field by providing optimum estimates using available parameters of the models and noise [43]. These include the Cubature Kalman filter (CKF) [44], the Unscented Kalman filter (UKF) [45], etc. Detection and sensing abilities are unique features of artificial intelligence tools, especially in autonomous driving, population counting, and agriculture, and different tools are available for that purpose [46]. However, unmanned aerial vehicles, UAV RGB, are cost-effective compared to other tools such as lidar [47], multispectral cameras [48], GNSS/INS systems [49], etc. The available object detection tools are designed for general purposes and can work on most platforms. However, most of these databases are facing challenges detecting smaller objects, in which tassel detection based on UAV is no exception. To have an improved tassel, it is necessary to have precise annotations and a versatile object detection algorithm. Therefore, a modified YOLOv5 architecture, called the YOLOv5 tassel, was developed to detect tassels [50].

1.5. Platooning

As the main contributors to the green gas effect, the sector of transportation is tasked with adopting sustainable approaches for enhanced operations, thereby reducing exhausts which contribute to pollution in general [51]. The development of truck platooning contributes a lot in this regard and champions the aim, thereby optimizing fuel consumption, and reducing air pollution and the decongestion of traffic [52]. However, the platooning system is disadvantaged by the issue of inter-vehicle distancing, which is influenced by the aerodynamic drag coefficient of the vehicles [53]. Numerous models have been developed and implemented in smart cities to minimize the aerodynamic drag coefficient. The work of [54] was prominent, which utilizes the predecessor-following architecture to track the desired distance while reducing the estimated aerodynamic drag coefficient to seek the optimal value. Also, the improved and advanced truck platooning, called automated truck platooning, which utilizes the Intelligent Transportation System for its work, is essential to the ever-growing freight market in the world [55].

2. Models and Advanced AI Algorithms for Analysis of Traffic in Smart Cities

2.1. Models for Analysis of Traffic in Smart Cities

The exponentially growing trend which leads to coupling interdisciplinary research has poised the implementation of AI tools in transportation engineering. Also, conventional and classical statistical tools such as linear regression were employed for attending to real-world problems, which are now on the verge of becoming obsolete due to their limitations in solving certain problems; however, with the advancement of technology, complex problems, which are mostly related non-linearly, are evolving especially in traffic engineering, which requires certain and special treatment [56]. However, before commencing the modeling of any data, there is a need to thoroughly understand the properties of data, as the work of [57] has broadly explained the stages needed for how the data mining and analysis are carried out, which includes (i) business understanding; (ii) data understanding; (iii) data preparation; (iv) modeling; (v) evaluation; and (vi) deployment, which can be equally applied to transportation problems. These were grouped and termed the Knowledge Discovery in Database (KDD).

In traffic analysis, traffic models are divided into microscopic, macroscopic, and mesoscopic, as shown in Figures 2 and 3.

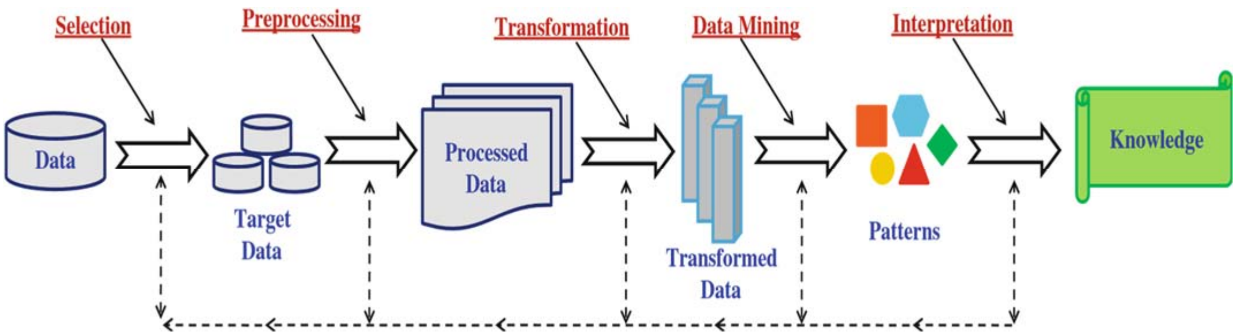

Figure 2. Architectural workflow of the KDD process [58].

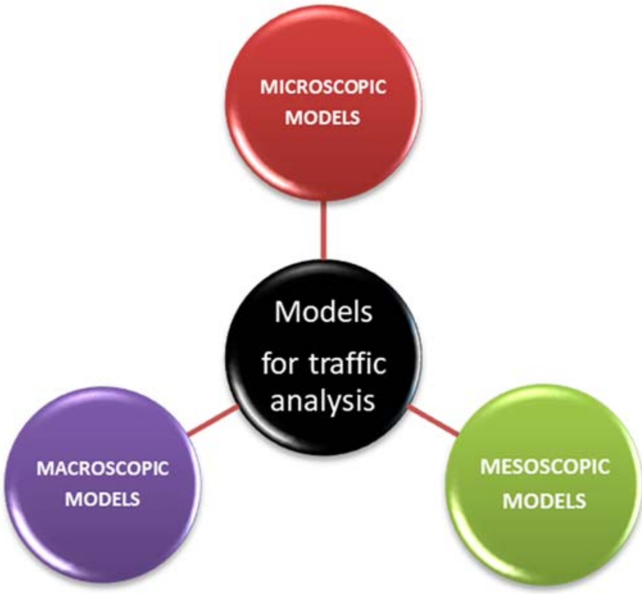

Figure 3. Models for traffic analysis.

The microscopic models for traffic management usually give a convincing relationship between vehicles, commuters, and road networks, which mainly depends on the robustness of the available data. In contrast, macroscopic models establish a mathematical relationship using the density and flow of traffic streams through the combination of microscopic traffic flow models and converting entity characteristics [59]. The mesoscopic models work on the distribution probability by providing details and describing the nature of traffic. They were subdivided into cluster and kinetics models [60]. The models developed for hybridized traffic simulation are currently emerging tools for analysis and simulation, and numerous researchers have developed a handful of soft tools for analyzing such traffic behavior, which is expected to be common in the current trend of smart city development.

Also, the recent trend of advanced technologies has erupted in all professional sectors, including transportation, whereby automobile-connected vehicles are rapidly emerging. Implementing these newly emerging technologies will give an unprecedented advantage to dwellers of smart cities; this is because most of the infrastructural development of smart cities is digital. Therefore, the transportation systems should be upgraded in line with the benchmark for the development of smart cities. However, a continuous acquisition of them will present unusual problems within traffic, which might be difficult to attend to as a result of mixtures and hybridized types of vehicles [61–63]. These connected automated vehicles (CAVs) are rapidly evolving across developed countries, making the stream of traffic heterogeneous, i.e., human-driven vehicles (HDVs) and connected automated vehicles. Therefore, a smart city will accommodate hybrid traffic formed of both types of vehicles [64]. A stochastic model was used by [65] to analyze the penetrating effect of CAVs on existing conventional traffic; they presented a fairly agreeable result which indicates that the introduction of such CAVs into the flow stream of HDV will improve traffic congestion characteristics and help in reducing other uncertainties related to HDV drastically. A heterogeneous mixed model was also developed to conceive the nature of traffic composed of HDVs and CAVs. The model considers critical parameters related to traffic analysis, such as speed, acceleration, and distribution related to the proportion of CAVs in the conventional stream of traffic. The presented results gave an insight into the advantages of developing CAVs, which will enhance traffic flow, bring stability, and reduce accident potentials due to planned human activities [66].

Among the models, the work of [59] presents a microscopic model for the analysis of traffic congestion caused by a hybrid formation of vehicles. These models include the automated cellular model and the car–follow model, which focus on solving problems arising from traffic mixed with CAVs and HDVs, to effectively improve traffic flow, safety, and the minimization of accidents. However, these micro-simulation approaches are attributed to a low output efficiency. To improve efficiency, another model was developed, called the transmission model, to alleviate these disadvantages through the microscopic model in the analysis of mixed traffic; the model developed proved to be more convincing in terms of speed and congestion prediction using the Cell Transmission Model (CTM) [67]. Different scholars [65,68,69] also employed CTM for traffic simulation and analysis; it serves as a promising tool for reliable, efficient, and effective modeling of traffic flow and characteristic analysis.

The mixed traffic model developed using PTV VISSIM software which analyzed mixed traffic using reaction time, led them to develop a fundamentals diagram of mixed traffic flow and the penetration effect of CAVs into the conventional stream of traffic [70]. To improve vehicle-to-vehicle (V2V) communication in smart cities, a control vehicle formulation was introduced using a control variable, employing a stream of traffic without changing the speed [71]. They used frequency domain analysis to optimally obtain the stability of the traffic conditions and consider the safety parameters of autonomous vehicles [72]. Although, these connected automobile vehicles were built with vehicle-to-vehicle V2V communication features, with a proper integration of these features into other smart infrastructures of smart cities, a challenging task may still need to be overcome, leading to difficulties in the decision-making approach to traffic in smart cities [73,74]. Due to the effect of over-speeding on most freeways, ref. [75] introduced a speed limit by employing the shockwave theory. The application is to have a manageable means of presenting the relative speed framework in smart cities. Establishing and optimizing control flow parameters is also reliable by optimizing control inputs. In this regard, predictive traffic controllers were used for this purpose [76]. Due to the uncertainties attributed to the heterogeneous mixture of traffic, traffic demand can be predicted by employing the speed limit control model [77]. The ultrasonic controller system model was used for traffic simulation at intersections and for detecting road regulation defaulters [78]. An IoT-based intelligent traffic controller was developed using centralized and non-centralized servers for controlling real-time traffic [79]. Traffic monitoring and priority scheduling IoT-based surveillance were developed for traffic management in signalized intersections; the data collected from IoT devices will be sent to the next signal and later to the server for any adjustment and recommendations [80].

2.2. Application of an Advanced AI Algorithm to Smart Cities' Operation

Marine activities (offshore, port, and landside operations) [81,82] in smart cities have to be supported with advanced simulation algorithms for smoother and proper operations [83]. These can be attained seamlessly by minimizing the cost incurred during berth scheduling, using a universal island-based metaheuristic algorithm (UIMA) which gives an optimal solution to the challenges associated with berth scheduling compared to other models [84]. Also, enhancing the operational planning of activities within berth scheduling at the seaside related to delay due to the continuous growth of marine activities, can be achieved through implementing a self-adaptive evolutionary algorithm (SA-EA), which describes the turnaround time and total weighted vessel late departures linearly [83]. Apart from marine operational activities, an important area where strengthening activities is a prerequisite to the sustenance of transportation in smart cities is inland logistics and supply chain management. The most common and conventional means by which stakeholders in the supply chain adopt enhancing the effectiveness of the supply chain is cross-docking terminals (CDTs); this is due to their operational flexibility [85]. However, this approach is associated with certain challenges in properly scheduling inbound and outbound trucks [86]. These challenges were studied and addressed, and an adaptive polyploid memetic algorithm (APMA) was deployed, which uses parent chromosomes as inputs and offspring chromosomes as the output. It gives a relatively better outcome than most common metaheuristics approaches used in logistics and supply chain management [87].

3. Traffic Management as a Decision-Making Process

Despite the fact that during traffic management analysis, the selection of a suitable model having generalized features within particular scenarios, remains the greatest challenge. Therefore, adequate knowledge and the nature of data should be studied thoroughly to use it. The difficulties that arise from developing a harmonized model of a particular set of data are due to the heterogonous and complex nature of traffic congestion; as a result, most algorithm-based models have limited capabilities [88]. This traffic feature makes decision-making a phenomenon rather than as a simulation phenomenon. In some circumstances, real-time and proactive approaches are more effective than analysis-based approaches [88]. As decision-making approaches suit most of the problems associated with traffic challenges, real-time information collection, transmission, and interpretation are crucial in smart cities; therefore, IoT will play a vital role. It will require cloud computing and compatible devices to compose tasks by working based on radio frequency identification (RFI) [89], as the work of [90] justifies.

3.1. Installation of Inductive Loop Detectors and Short-Range Communication

Loop detectors are part of intelligent devices that collect efficient and accurate real-time data for effective and efficient traffic management, usually installed on highways, expressways, and intersections with relatively high traffic volumes. The detector models have been tested on some roads of Johannesburg, as the work of [91] outlines.

3.2. Short-Range Communication

As another system that helps in decoupling the expected congestion in smart cities, direct communication between vehicles or road-to-vehicle, or road users to vehicles will be supported and facilitated with the help of short-range and robust wireless communication systems. These wireless communication systems will detect accidents, traffic regulation violations by drivers, congestion ahead that may disrupt effective road usage and alert the road user for a proper and urgent resolution.

3.3. Pedestrian Detection Systems

Most roads in urban centers, especially in developing countries, need the proper provision for protecting the rights of pedestrians. Therefore, installing such sophisticated devices will give an avenue to protect pedestrians from the potential dangers of vehicles along the roads. The data recorded will be transmitted to the road safety authorities for regulations. Another advantage of IoT-based devices is their ability to have secured data storage in cloud storage for further usage and analysis, as presented by [92]. The deployment of such devices can give certain and dependable means to the commuters on the real-time traffic and the massive data gathered from roads, which includes those from loops coils, intelligent video cameras, and sensors, called big data in traffic engineering, although these devices used for collecting data in cities are expensive and at times have some disadvantages under extreme weather conditions. However, these challenges can be seamlessly managed with the support of the internet and other advanced technologies [85]. Overall, proper traffic management in smart cities involves overlapping three layers. These layers are:

i. Physical layer: This consists of physical parts of the systems, which are composed of smart devices and agents which are normally located within strategized locations along the roads for sensing, recording, and collecting information from roads, road users, and vehicles, and these data and information will be uploaded to the cloud with the help of a strong network connection.

ii. Network layer: Uploading and transmitting specified data of interest by the traffic officials is carried out by using a network layer; the uploaded data can be used to give a wider range of applications to road users.

iii. Application layer: This is usually a software which feeds with the information received from the first and second layers to assist road users with the real-time traffic condition of the cities.

4. Framework/Performance Measures for the Proper Management of Traffic in Smart Cities

As part of the best practice of a sustainable decision-making process for sustainable transportation, obtaining reliable performance measures can be achieved by integrating, planning, and programming the concept of sustainability. These performance measures could help establish the framework, aid in appraising projects, and track the level of functionalities and their acceptance by the public [93]. These performance measures have a direct influence on traffic management in smart cities. However, failure of their proper implementation will lead to having a more complex system where management will be difficult. These performance measures include.

4.1. Land Use Visioning/Scenario Planning

As employed by some developed metropolitans, this approach will equally serve as a tool to reach a real consensus in predicting smart future growth and land allocation to specific and crucial activities in the cities, such as crucial infrastructures, including transportation infrastructures, environmental leisure parks, residential and industrial areas, which will be used to have a direct or indirect insight into producing preliminary guidelines for future development.

4.2. Long-Term Transportation Planning

Upon developing a wide range and flexible land use in smart cities, it is of great importance to prioritize long-term planning and decision-making for the transportation planning of a city. Comprehensive results obtained from long-term transportation planning will give a straightforward approach to identifying and establishing a framework for proper decision-making by the transportation authorities.

4.3. Corridor Studies Programming

In most rural areas, corridor studies are regarded as long-term planning due to limited infrastructural development, with fewer expectations of rapid growth. However, in smart cities, this should be carried out independently to establish well-balanced allocations and purposes for land use. Although it can be executed simultaneously with long-term transportation planning, the aim of the corridor study is to have decongested streets with full accessibility and proper mobility for road users, which leads to a proper traffic management.

Proper and sufficient funding for transportation infrastructures should be given special attention. The return of investment and benefit–cost metric are the two major parameters used to establish the projected funding of transportation infrastructures. This entails presenting, sorting, and analyzing the future project and its relative impact before implementation.

4.4. Environmental Review and Performance Monitoring

Some transportation infrastructures are virtually feasible. However, their physical implementation will render the environment vulnerable to some nuisance threats, violating the sustainability aim. Therefore, for future transportation decisions, especially in smart cities, a proper environmental assessment should be carried out before commencing design and construction. A timely performance assessment of the already built transportation infrastructures will present an overview of congestion, pollution, and other associated factors that negate smart city development. These periodic performance assessments will create a competitive advantage for other regions.

5. Conclusions

Smart cities require robust and flexible transportation approaches integrated with state-of-the-art artificial intelligence infrastructures. However, managing traffic congestion is a complex task due to various factors influencing it, such as time and rate dependency. To effectively manage traffic, it is necessary to identify the causes of congestion, traffic flow, occupancy, and destination. Smart cities were built with the leveraged provision of AI-related devices, such as physical and vision-based cameras, etc., commonly used to obtain the required information.

This paper explains how real-time traffic data, vehicle, and road user information are collected using AI sensors and other ITS-based devices. The mechanism of processing and transmitting the already collected data using machine learning algorithms and cloud computing, by which the resulting outcomes are used to develop models and decision-making approaches for managing traffic in smart cities, have been also been explored in this research. These approaches enable proper traffic management, decision-making policies, and documentation for future use. They also allow for the prediction of traffic outcomes, traffic forecasting, traffic decongestion, minimization of road users' lost hours, suggesting alternative routes, and simplifying and smartening transportation activities for urban dwellers. In addition, as the pivot of this paper, sustainable framework/performance measures have been presented to make traffic simulation and real-time decision-making easier. By utilizing these holistic approaches, new transportation systems in cities can be established, and the existing ones can be improved by making them more efficient, ultimately leading to a better quality of life for dwellers.

Author Contributions: Conceptualization, A.A.M. and F.A.; Methodology, A.A.M. and S.I.M.; Validation, W.O. and M.A.; Data curation, M.A.; Writing—original draft, S.I.M. and F.A.; Writing—review & editing, F.A., W.O., M.A. and S.I.H.; Project administration, S.I.H. All authors have read and agreed to the published version of the manuscript.

Funding: The authors extend their appreciation to the Deputyship for Research & Innovation, Ministry of Education in Saudi Arabia for funding this research work through the project number 223202.

Institutional Review Board Statement: Not applicable for studies not involving humans or animals.

Informed Consent Statement: Not applicable.

Data Availability Statement: The research is focused on reviewing and establishing framework for management of traffic in smart cities. Therefore, no data available to be accessed publically.

Conflicts of Interest: The authors declare no conflict of interest.

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