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SURVEY

Ridesharing and Crowdsourcing for Smart Cities: Technologies, Paradigms and Use Cases

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ABSTRACT Recent technology developments and the numerous availabilities of mobile users, devices and Internet technologies together with the growing focus on reducing traffic congestion and emissions in urban areas have led to the emergence of new paradigms for ridesharing and crowdsourcing for smart cities. Compared to carpooling approaches where the driver and participant passengers or riders are usually prearranged and the journey details known beforehand, the paradigm for ridesharing requires the participants to be selected at short notice and the rider trips are often dynamically formed. Crowdsourcing techniques and approaches are well suited to match drivers and riders for these dynamic scenarios, although there are many challenges to be addressed. This paper aims to survey this new paradigm of ridesharing and crowdsourcing for smart city transportation environments from several technological and social perspectives including: 1) ridesharing and architecture in transportation; 2) techniques for ridesharing; 3) artificial intelligence for ridesharing; 4) autonomous vehicles and systems ridesharing; and 5) security, policy and pricing strategies. The paper concludes with some use cases and lessons learned for the practical deployment of ridesharing and crowdsourcing platforms for smart cities.

INDEX TERMS Artificial intelligence, crowdsourcing, deep learning, machine learning, ridesharing, transportation, smart cities.

I. INTRODUCTION

Recent technology developments and the numerous availabilities of mobile users, devices and Internet technologies together with the growing focus on reducing traffic congestion and emissions in urban areas have led to the emergence of new paradigms for ridesharing and crowdsourcing for smart cities. These paradigms are driven by the convergence of various trends including: (1) The economic and financial imperatives to reduce traffic congestion for transportation in urban areas and smart cities; (2) The rise of crowd-based capitalism and the sharing economy (e.g., Uber, Airbnb, WeWork) [1]; and (3) The environmental and health policies and targets to reduce traffic emissions and air pollution [2], [3]. There is a growing trend in many countries to utilize ridesharing as one of its mechanisms to meet its respective global reduction targets for carbon. The authors in [4] investigated and quantified the benefits to the environment and estimated the amount of CO_2 emissions saved by ride-sharing for the city of Dublin. For a scenario of ridesharing for five days a week, the authors estimated that 12,674 tons of CO_2 emissions could be saved with a reduction of 68.2 million km saved in total trip journeys each year.

Ridesharing is a new paradigm with several definitions in the literature. The authors in [5] give a definition of ridesharing as ''Ridesharing refers to a mode of transportation in which individual travelers share a vehicle for a trip and split travel costs such as gas, toll and parking fees with others that have similar itineraries and time schedules''. The authors in [6] give a basic definition of ''ridesharing platforms connect drivers and vehicles with consumers who want rides at an agreed price''. The challenges for ridesharing can be

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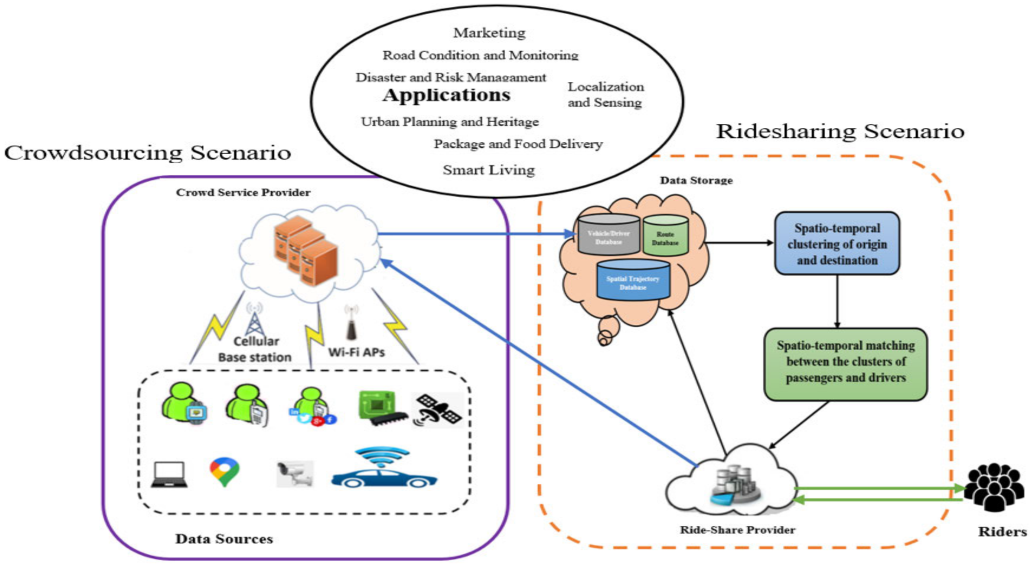


FIGURE 1. Overview of relationship between ridesharing and crowdsourcing.

contrasted with that for conventional carpooling. Compared to carpooling approaches where the driver and participant riders are usually prearranged and the journey details known beforehand, the paradigm for ridesharing requires the participants to be selected at short notice and the passenger trips are often dynamically formed. These dynamic scenarios and varying environments for ridesharing require the development of new techniques and approaches to be created and new challenges and scenarios to be addressed.

There are three entities in a typical dynamic ride-sharing scenario: (1) Driver; (2) Passenger or rider with GPS-enabled smartphone; and (3) Ride-share provider. The rider sends a request to the ride-share provider and gives his or her current location as the trip origin and the desired destination. The ride-share provider performs the matching algorithm with the drivers in its database, and attempts to perform a match for the request. The ride-share provider then sends the proposed arrangement to the driver and passenger. Some challenges for ride-sharing would be to develop new techniques for handling the large, varying and dynamic nature of the spatial-temporal driver and passenger data. These challenges would include: (1) Development of efficient computation techniques for data analytics for travel and mobility patterns; (2) Development of large-scale sensing systems in urban areas and smart cities to capture the dynamic and changing driver and passenger data; and (3) Development of techniques for combining data and fusion of the varying and heterogeneous data from multiple data devices and sources to optimize travel paths and journeys. Some examples of these data sources are smartphones and personal devices, data from GPS devices and tools, traffic cameras and roadside devices and satellite and geoinformation data sources. Recently, crowdsourcing techniques and approaches have become pervasively available to address challenges encountered in smart cities.

The concept of crowdsourcing is a sourcing model or technique that utilizes human interaction for widescale collection of data in pervasive environments. It involves the collection of information including ideas, opinions, micro-tasks or work from an evolving group of participants. Traditional crowdsourcing mechanisms usually source data via the fixed Internet and infrastructure sensors, which are either centralized or static. In recent years, a new model termed as mobile crowdsourcing has been proposed to enable people to share and collect data. The key characteristics of mobile crowdsourcing are mobility, collaboration and human capacity. In contrast to traditional crowdsourcing, mobile crowdsourcing integrates the benefits of ICT and wireless communications in urban scenarios including traffic planning, safety and social recommendation. The authors in [7] discussed the relation between the ridesharing and crowdsourcing tasks in the physical world using time and location as the context. Fig. 1 shows an overview of the relationship between ridesharing and crowdsourcing platforms and its application areas.

This paper aims to survey these new paradigms for ridesharing and crowdsourcing for smart city transportation environments from several technological and social perspectives. The paper will discuss how (mobile) crowdsourcing can be effectively utilized to meet the challenges for efficient ridesharing platforms and are well suited to match drivers and passengers for dynamic scenarios. Mobile crowdsourcing can be efficient solutions to solve the issues for dynamic ridesharing and user groups but requires the coordination and management challenges to be effectively addressed. For ease of discussion, we have identified and categorized these challenges as being related to ridesharing and architectures in transportation systems, techniques for ridesharing (e.g., matching and clustering), application of artificial intelligence for ridesharing, vehicles (taxi and bus) ridesharing deployments, ridesharing systems for autonomous systems, and security, policy and pricing strategies. The paper concludes with some use cases and the lessons learned for the practical deployment of ridesharing and crowdsourcing for smart cities.

There are some other surveys and earlier works for crowdsourcing, ridesharing and transportation which can be found in [5], [8], and [9]. Compared to other and earlier works, this paper makes comprehensive contributions to ridesharing and crowdsourcing for smart cities from several different aspects:

- The review covers a wide spectrum of enabling technologies for ridesharing and crowdsourcing architectures in transportation systems. Different types of architectures, techniques and application of artificial intelligence (AI), machine/deep learning and swarm intelligence approaches are discussed. We also include new paradigms covering models and architectures for vehicular-based crowdsourcing and vehicle social networks for smart city applications;
- The review covers the emerging paradigms such as the utilization of autonomous vehicles and systems for ridesharing. There are many more papers discussing ridesharing using driver-operated vehicle platforms compared to using autonomous vehicle platforms. We attempt to give a balanced coverage for the different platforms;
- The paper covers both technological and social aspects for ridesharing and crowdsourcing for smart cities transportation. The technological aspects include coverage for both passengers' transportation and goods/freight. Joint optimizations using ridesharing approaches to transport passengers and goods are discussed to maximize benefits for smart city environments. For the social aspects, the paper discusses the security, policy and pricing mechanisms;
- To aid transportation and smart city designers, the paper gives a comprehensive roadmap (Fig. 2) showing an overview of the classification descriptors which are covered in this paper. The paper covers over 170 reference works with a focus on recent works and is complemented by summary tables in different sections with the aim to serve as a comprehensive reference point for researchers and readers towards further and future works. Databases including IEEE Xplore and Elsevier were searched for the data collection and review.

The remainder of the paper is organized as follows: Sections II and III gives initial discussions for ridesharing and crowdsourcing architectures in transportation focusing on models and network topologies. Discussions for the new paradigms for autonomous vehicles and systems for ridesharing are included in Section II. Next, Section IV expands the discussions for different types of algorithms and techniques for ridesharing. Emerging paradigms such as AI and machine learning for ridesharing are discussed in Section IV. Social aspects for ridesharing are discussed in Section V. Sections V-A and VI discusses some use cases and applications for ridesharing and crowdsourcing in smart cities. Section VI-F gives some concluding remarks.

II. RIDESHARING MODELS AND ARCHITECTURES IN TRANSPORTATION

Ridesharing can be considered as a shared service. Ridesharing services and models can take various forms and include taxi ridesharing, carpooling, slugging and bus pooling. Taxi ridesharing receives passengers ride requests in real-time via smartphones, accepts the requests and send the right taxis to pick the passengers. Unlike real-time taxi sharing, carpooling is usually a smaller size of the problem, and ride requests are known in advance. Slugging [10] is a variation of rideshare commuting where one passenger abandons his trip and merges or joins the trip of another passenger. Hitchhiking is a form of ridesharing that the passenger attempts to get a free ride or lift from another traveler. The idea of ridesharing can also be extended to public transport buses, called bus pooling. Compared to carpooling, bus pooling offers higher capacity and lower cost. Different from traditional bus services, bus pooling provides flexibility and convenience to passengers by reducing the time or distance. This section discusses important factors for ridesharing design models, architectures and implementations in transportation. The section is structured into four sub-sections. Section II-A will discuss the various designs for network topologies and architectures. Sections II-B to II-D discusses various design models including taxi models, bus models and autonomous models for ridesharing. Table 1 shows a summary of ridesharing models and architectures in transportation discussed in the subsection.

A. NETWORK TOPOLOGIES AND ARCHITECTURES

A first important factor for ridesharing is the network topologies to be designed and implemented. There are various network topologies which can be utilized such as ring, star and grid topologies. The authors in [11] investigated the role of the network topology for on-demand ridesharing systems. In this work, the authors utilized a basic model to study the network characteristics for ridesharing. Their model utilized a structure where the street network was modeled as a graph with N nodes. The ridesharing requests are modeled as a request pattern $P_{i,j,t}$ where a request is denoted as an ordered pair (i, j) of a pick-up node i and a drop-off node j from a request pattern at time t. The ridesharing requests are modeled as a Poisson process according to a dispatcher algorithm. Their work found that there were significant performance differences for ridesharing among networks with various dimensions (one dimensional ring structure, two-dimensional grid structure and n-dimensional star structure) and the number of nodes had a substantial impact. The authors also concluded that ride-sharing is topologically challenging in urban locations (with grid-like structure) as routes are more likely to be distinct.

The authors in [12] investigated the relationship between the ridesharing network structure and its benefits. Their

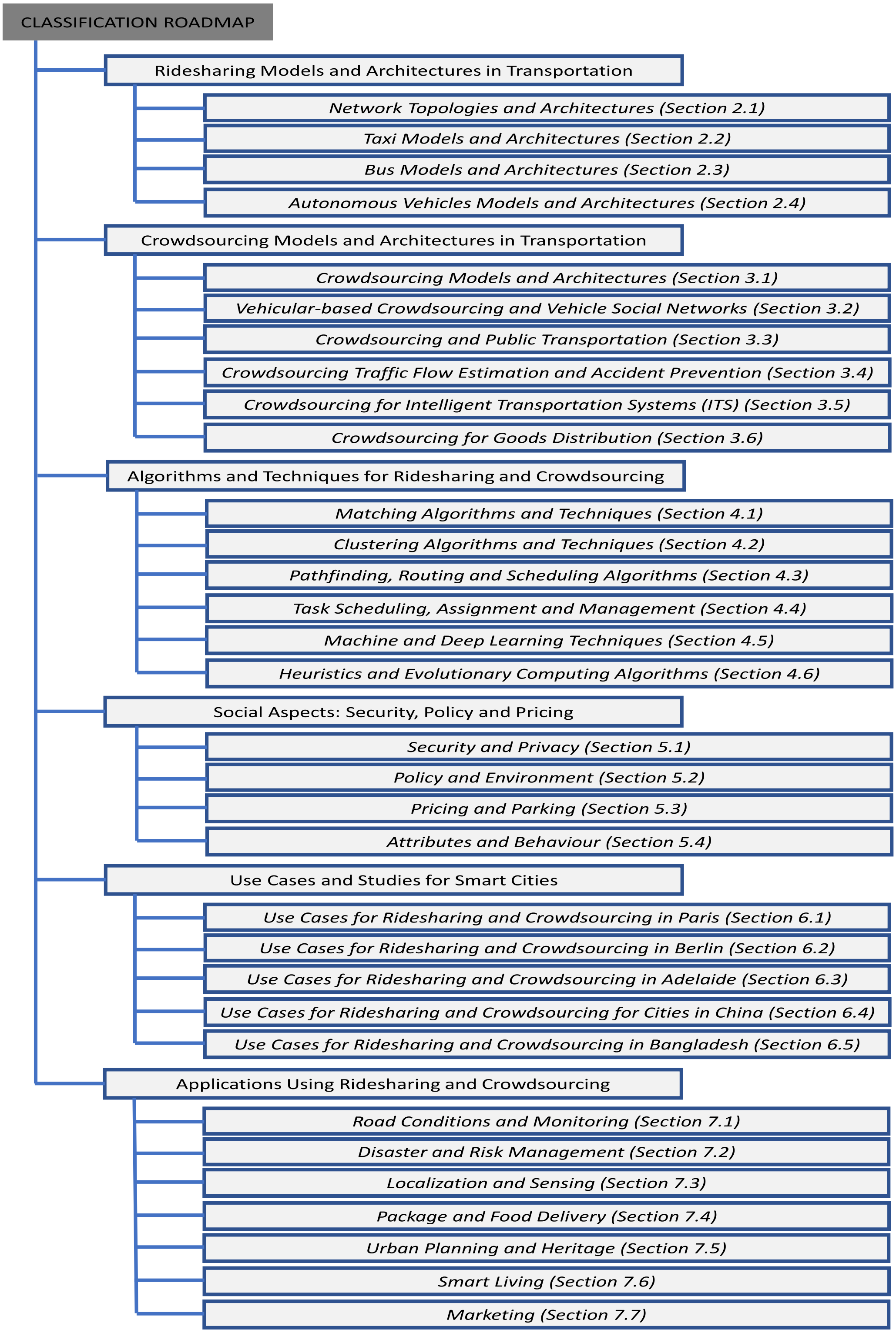


FIGURE 2. **Survey roadmap showing classification descriptors covered in this paper.**

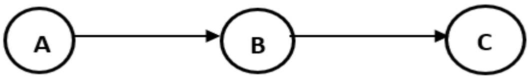
study used a dataset of 14 million taxi trips in New York in the year 2013. Their work identified seven network topological features that could be used to predict the benefits: (1) Number of nodes; (2) Number of edges; (3) Averaged degree centrality score; (4) Averaged betweenness centrality score; (5) Averaged closeness centrality score; (6) Averaged eigenvector centrality score; and (7) Density Score. The authors in [13] proposed a multi-class ridesharing user equilibrium assignment framework which incorporates various travelling scenarios and policy measures such as vehicle

TABLE 1. Summary of ridesharing models and architectures in transportation.

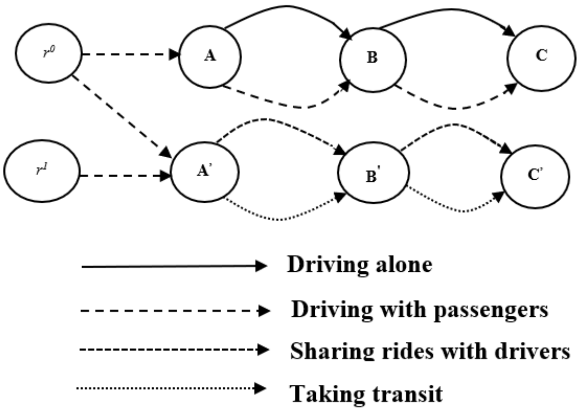
Focus area	Work contributions	References
Network topologies and architectures	Network topology for on-demand ridesharing systems	[11]
	Relationship between ridesharing network structure and benefits	[12]
	Framework to model ridesharing and transit door-to-door services	[14]
	Network traffic assignment model for ridesharing with real-time ride-matching	[15]
Taxi models and architectures	Centralized taxi scheduling model using real-time transfer system for ridesharing	[16]
	Cloud-based architecture for taxi ridesharing system	[17]
	Grid-based model and architecture for dynamic taxi ridesharing	[18]
	Taxi scheduling model and architecture for dynamic ridesharing	[19]
	Taxi-sharing problem as example of the Dial-a-Ride (DARP)	[20], [21], [22]
Bus models and architectures	Framework and architecture for large-scale bus ridesharing/pooling	[23]
	Dynamic bus routing model and simulator	[24]
	Bus ridesharing model which combines different approaches (e.g., slugging and hitchhiking)	[25]
Autonomous vehicle models and architectures	Space Time for Autonomous Ridesharing Systems (STARS)	[26]
	P2P system model and shared autonomous fleet vehicles (SAFVs) for ridesharing	[27]
	Ridesharing interactions between dynamic routing and optimization fleet size, road networks for shared autonomous vehicles	[28]
	Discrete-time shared autonomous electric vehicles (SAEV) simulation model with rideshare matching	[29]
	Universal Design (UD) model and shaping urban public transport with ridesharing	[30]

tolling, restrictions and subsidization into the network architecture. Fig. 3(a) shows the original network structure and Fig. 3(b) shows some of the extended scenario topologies which were considered: (1) Driving alone; Driving with passengers; (3) Sharing rides with drivers; and (4) Taking transit. In their network architecture, each link in the original network can correspond to four different links in the extended ridesharing network. The drivers and passengers can switch roles e.g., solo to ridesharing drivers or ridesharing passengers to transit. In their experiments, the authors formulated the problem as a mixed complementary problem and performed simulations using the Sioux-Falls dataset network to verify their approach.

The authors in [14] proposed a general framework to model ridesharing and transit door-to-door services. Their approach can be used to model demand-responsive transit systems including ridesharing, dial-a-ride and non-shared taxi services. Comparisons can be made among various urban modes of transportation, city topologies and demand levels. Their approach utilized differential dynamic equations to track state vectors of vehicles over time in the transit system. Their architecture also allowed for the modifications of



(a) Original graph scenarios for ridesharing topologies.



(b) Extended graph scenarios for ridesharing topologies.

FIGURE 3. Original and extended scenarios for ridesharing topologies [13].

vehicle workloads in three ways: (1) Through an assignment; (2) Through a pickup; and (3) Through a drop-off.

Another area of research for network architectures and topologies which has been proposed by researchers is termed the traffic assignment problem. This problem aims to examine the network performance (e.g., due to congestion levels) and determine the optimal traffic flow patterns for ridesharing drivers and passengers. The authors in [15] proposed a network traffic assignment model for ridesharing with real-time ride-matching. In their approach, ridesharing drivers and passengers shared the same origin-destination (OD) pairs. The travel demand is modeled as a function of a fee termed as the "ridesharing price". This function is utilized to model the compensation to the drivers for the extra cost and inconvenience. Their approach combined a ridesharing market model with a traffic equilibrium model. Their experimental results showed the following outcomes: (1) The ridesharing base price influenced the congestion level; (2) An increase in price may reduce the traffic congestion within a certain level; and (3) The utilization of ridesharing increased as the congestion increased.

B. TAXI MODELS AND ARCHITECTURES

This sub-section gives discussions for taxi models for ridesharing in transportation. Taxis are a major form of transportation in urban environments and smart cities. There are various challenges to be addressed for the design of optimal transportation systems. During peak periods, passengers may need a significant waiting time. However, increasing the number of taxis may increase traffic congestion and energy consumption. A potential solution which has not been thoroughly investigated is through ridesharing using public taxis and/or private vehicles. Taxi models and ridesharing can be categorized into two types: (1) Real-time ridesharing systems; and (2) Options and models for different constraints. The first category aims to design or develop real-time approaches including matching algorithm which can rapidly find the right vehicle to satisfy the requests. The second category focuses on the combination optimization by considering different constraints, for example, price, waiting time, route, scheduling, and payment, etc.

The real-time taxi-sharing is a challenging problem because the routes can continuously change, and ride requests need to be generated in real-time. However, due to the sparsity of vehicles available on the road, the service quality of the ride may be low. Each passenger could only take one vehicle from point A (origin) to point B (destination) resulting in one-hop delivery. Some of the solution offered by researchers to these challenges have focused on designing optimal scheduling and transfer mechanisms. An illustrative approach for a centralized taxi scheduling using a real-time transfer system for ridesharing services can be found in the work by [16]. Their approach has three components: (1) Passengers – make requests and trace routes using a mobile app; (2) Server – receive requests, performs computations and dispatch vehicles to serve passengers; and (3) Taxicabs – receive instructions from server and update information. They formulated mathematical equations to calculate the travel time on the road segments and the detour time ratio of the request, and the path planning is based on the Dijkstra algorithm. Their experimental results using simulation data from road networks of Manhattan demonstrated that the real-time system could improve the efficiency of traffic by using the trajectory of vehicles in the ridesharing system. However, their experiment was performed in an environment with connected and self-driving vehicles.

The authors in [17] proposed a cloud-based approach for real-time city-scale taxi ridesharing. Fig. 4 shows the cloud-based architecture for the ridesharing system which utilizes multiple servers to perform the administration, computation and storage. Their approach utilized passenger smartphones to make the real-time ride requests and incorporated factors such as time, capacity, incentive mechanisms and monetary constraints into the models. The road network is modeled and partitioned using a grid. The road network node closest to the geographical center of the grid cell is selected as the anchor node for the cell. Each ride request contains the trip origin and destination, and time window constraints for the pickup and dropoff. Their experimental results showed that the proposed system gave savings of 7% average fare for riders. The authors also compared the performance of single-side and dual-side searching algorithm in the scheduling algorithm (first-fit and best-fit). Their experimental results showed that the dual-side taxi searching algorithm could reduce the computational requirements by 50% when compared to the single-side taxi searching algorithm.

The authors in [18] proposed a grid-based model and architecture for dynamic ridesharing. Their work presented a ride-sharing algorithm termed as Dynamic Grid Scheduling Algorithm (DGSA) which utilizes a spatial index list to

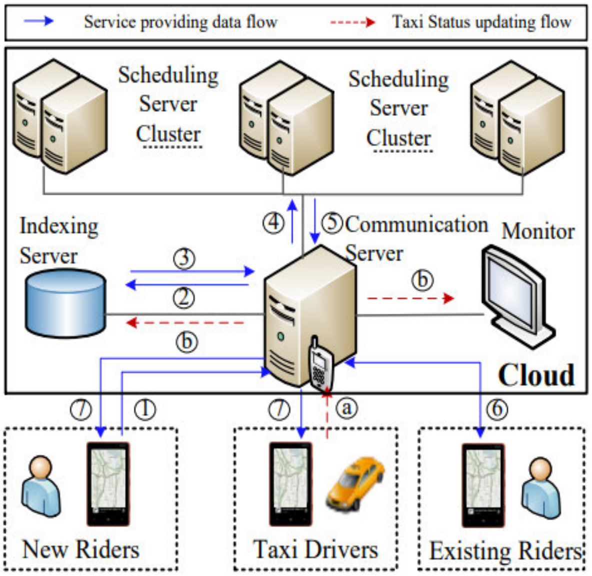


FIGURE 4. Cloud-based architecture for taxi ridesharing system [17].

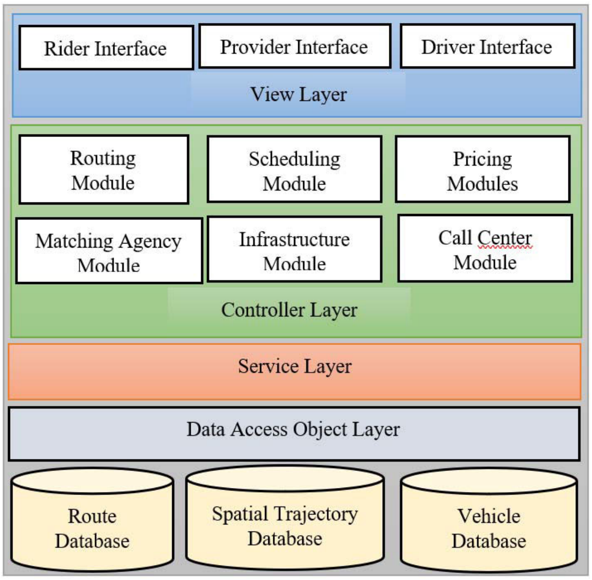


FIGURE 5. Framework of the large-scale bus ridesharing/pooling [23].

reduce the size of taxi candidate sets, and dynamically adjusts the grid size for various road conditions to locate the taxi closest to the request. Their experimental results using dataset from the Beijing Chaoyang district showed that savings of 35.5% computation could be achieved without reducing the average satisfaction.

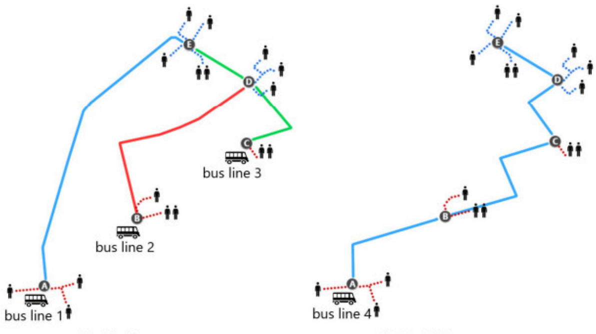
The authors in [19] investigated the problem of taxi scheduling models and architectures for the dynamic ridesharing service. The architecture contains several components: (1) Information Platform – receives the trip request and tracks the status for each taxi (taxi identifier, current time, taxi, current location, current taxi capacity and taxi on-duty route); (2) Cluster and Match module – cluster and assign rider requests, and gives notification of matching results; (3) Correlated Pooling – performs data collection and grouping of correlated rider requests; (4) Adjacency RideMatching – performs the balancing for taxi distributions; and (5) Demand Learning – performs the learning of the demand pattern based on historical data. Their experimental results utilized datasets from the city of Chicago. Their study analyzed the threshold of correlated rider requests, and the average online running time.

Other works for models and architectures for taxi ridesharing can be found in the works by [20], [21], and [22]. These works model the taxi-sharing problem as a specific example of the Dial-a-Ride Problem (DARP). The DARP is a well-known NP-hard transportation problem which has been intensively investigated for static scenarios where all the rider requests are known apriori. However, fewer works have been reported for dynamic scenarios (dynamic DARP problem) where the rider requests are calculated and generated on-the-fly. There remains much research to be performed to investigate the factors affecting the dynamic nature of the taxi ridesharing models and architectures.

C. BUS MODELS AND ARCHITECTURES

Compared to taxi models for ridesharing, bus models and architectures for ridesharing aims to determine the optimal locations for pickup and/or delivery for a large number of passengers. The total sum of the distances for all passengers needs to be minimized to set up the new bus stop at the optimal location. Furthermore, bus pooling requirements also needs to satisfy the minimum loadable capacity. This is because having a larger number of passengers per shared vehicle can increase the long-term profitability. Some representative works for bus models and architectures for ridesharing can be found in [23], [24], and [25]. The authors in [23] proposed a large-scale bus ridesharing or pooling model and architecture which employs an online bus-hailing service to allow riders send requests using smartphones and wait for being collected by a public bus when the bus has gathered a sufficient number of riders. Fig. 5 shows the architecture and framework of the proposed bus ridesharing. The framework has two major components: (1) Matching module – which has the responsibility to analyze the spatial trajectory for the trips, and computes and identifies the similarity of spatial trajectories; and (2) Terminal module – which has the responsibility to compute the optimal pickup/delivery point for riders by using algorithms and location-based services. The system then notifies drivers and riders the outcomes including the waiting location in the time window. The authors proposed exact and approximate algorithms to optimize the ride-matching and maximize the success rate, and validated their work using real-world datasets from the city of Shanghai.

The authors in [24] developed a dynamic bus routing simulator which uses historical data from smartcards and applies a modified insertion algorithm to model the dynamic routes of the vehicles. The simulator output was designed to give



(a) Slugging (b) Hitchhiking

FIGURE 6. **Bus ridesharing model which combines: (a) slugging and (b) hitchhiking [25].**

the optimal routes which consistently changed in response to new information. After completing the simulation, the simulator returned metrics with: (1) Passenger experience (e.g., passenger waiting and travel time); and (2) Bus performance (e.g., distance travelled, occupancy rates, etc.). The authors work provided a case study for the city of Singapore.

The authors in [25] proposed an optimization approach to solve the problem of low vehicle utilization and maximize the success rate for ridesharing. In their approach, the authors developed a grid-based heuristic algorithm with performance guarantees for origin-destination (OD) pairs clustering. The authors proposed a novel bus ridesharing model which combines slugging and hitchhiking. Fig. 6 shows different solution approaches for slugging and hitchhiking. The figure shows three trips which have been scheduled from locations A to E, locations B to D, and locations C to E. The red dotted line shows the paths from the passenger origin to the departure stop. The blue dotted line shows the path from the alighting stop to the passenger destination. The slugging approach is utilized for a bus that has managed to gather sufficient OD pairs, and the hitchhiking approach is utilized otherwise. Their experimental results showed that their proposed hybrid approach could increase the success rate for the ridesharing system.

D. AUTONOMOUS VEHICLE MODELS AND ARCHITECTURES

This subsection discusses the new paradigms for utilization of autonomous vehicles (AVs) and systems for ridesharing. The AVs are designed with a focus on providing solutions to challenges regularly encountered by vehicle users. AV depends on the interactions between human intelligence and integrated sensors which generate data that translate into input used in decision making for different environment. The created interface becomes vital in mitigating the errors inherent in humans during road commute thereby reducing accidents. Autonomous vehicles promote ridesharing among passengers due to its ability to account for uncertainty in departure times even for people with identical residential and work locations. Manually driven vehicles are subject to schedules of the driver and hence lack equal flexibility.

An illustrative AV model can be found in the work by [26]. In this work, the authors proposed a multi-agent simulation architecture and platform termed as Space Time for Autonomous Ridesharing Systems (STARS). The STARS architecture is comprised of five elements (frame, time flow, data flow control, store and model) which finds useful application for the simulation of large-scale (e.g., smart cities) autonomous ridesharing systems. The research involved a simulation that was designed to create an understanding of the impact users' uncoordinated behavior exerts on participation in autonomous ridesharing was presented via an extensive experiment on STARS utilizing datasets obtained in real-world environments. The authors in this work demonstrated the impact of various configurations and parameters (size of fleet, vehicle capacity and waiting time) on overall efficiency due to poorly coordinated user behavioral patterns during ridesharing participation. The authors conducted experiments using various system configurations within the STARS simulation. The travel data used in the simulation was obtained from real-world taxi trips from the city of New York City. In STARS simulations, the applications are constrained to fixed portions of data over periods of time. Also, locally modified data for each time step are assigned to the shared data store. Movement of data in and out of the data store is executed using two declarative domain-specific languages: the first specializes in handling sets of objects. This is achieved by specifying the numerical operations on the data sets. The second functions by allowing and determining the direction of data flow. In STARS, there is an ordered sequential flow of communication between application layers creating predictable patterns of output which support the simulation components. The STARS simulation consists of several components with specialized functions such as request generation, component updates, data logging, a dispatching component, and a load rebalancing component. The dispatching component computes the optimal assignments by utilizing three dynamic tools (RV-graph generator, RTV-graph generator and the assignment optimizer). The purpose of the RV-graph generator is to determine which requests can be paired and allocate the optimal vehicles to service individual requests. The RTV-graph generator evaluates trip feasibility, determining what pairs can be combined for pickup by a single vehicle. The STARS platform operates on the principle of an object-oriented design capable of supporting simulations with different levels of complexity and scalability in a distributed, or multicore environment. The author recognized how these properties make for a good fit in autonomous ridesharing simulations.

The authors in [27] highlighted the limitations of peer-to-peer (P2P) ridesharing in providing assurance of matches in conditions of driver shortages. A solution of fleet service is proposed as a possible supplement for failures in P2P services. Autonomous vehicle has an advantage of greater passenger per vehicle ratio which offers opportunities in deployment of fleet transport systems. The research provides a model that integrates P2P system and shared autonomous fleet vehicles (SAFVs) for ridesharing. The authors also employ a dynamic programming tool to match riders to regular personal-auto drivers using peer to peer communication and a heuristic algorithm to match ride demand and supply. The heuristic algorithm searches out optimal size of fleet vehicles and best routes with a measure of the maximum capacity of passengers that may be accommodated by the system. Simulations to predict the total drive-alone trips the fleet system has been able to substitute. Through network links, information such as morning peak hours and its influence on travel times were updated to determine the positions of riders and vehicles within the time-expanded network. The study targeted the northern part of the state of Los Angeles, using data derived from the city of California data and demand model. An abstract network with 44 traffic analysis zones (TAZs) was built to obtain sufficient data points for reliable conclusions to be drawn.

The authors in [28] identified strategic and operational challenges in shared autonomous vehicles which were addressed in several literature with issues relating to strategic problems treated exclusively for the operational challenges. The author proposed a unified optimization framework that considers foundationally the interactions between dynamic routing and optimization of variables such as fleet size, road networks and parking space allocation for shared autonomous vehicles. The framework was tested against travel data from the New York City taxi database. The focus of the research offers a multi-dimensional perspective with a possible resultant effect of simultaneous reduction in travelers' commute times and total required travel distance and number of shared autonomous vehicles required. Within the strategic considerations is the cost for construction of infrastructure, this ensures that costs are considered on either side of both the user and the system alongside tradeoffs that may be required for sustainable performance. The multi-dimensional perspective desired in this research was synthesized using a unified multi-objective optimization problem (MOOP) framework. The authors conducted numerical experiment captured datasets surrounding zone of origin, destination, time of departure from point of origin, length of time spent travelling for each individual trip. For purposes of the research, three conditions were considered in as a representation of all possible ridesharing configurations. These include the no-ridesharing group ($\rho = 1$), two-person ridesharing group ($\rho = 2$), and five-person ridesharing group ($\rho = 5$). The comparison clearly showed the increased efficiency noticeable early on between the case studies for ($\rho = 1$) and ($\rho = 2$). The efficiency in total travel time almost doubles when measured for ($\rho = 1$) against ($\rho = 2$). These gains were also observed in infrastructure cost with incremental efficiency recorded even at ($\rho = 5$).

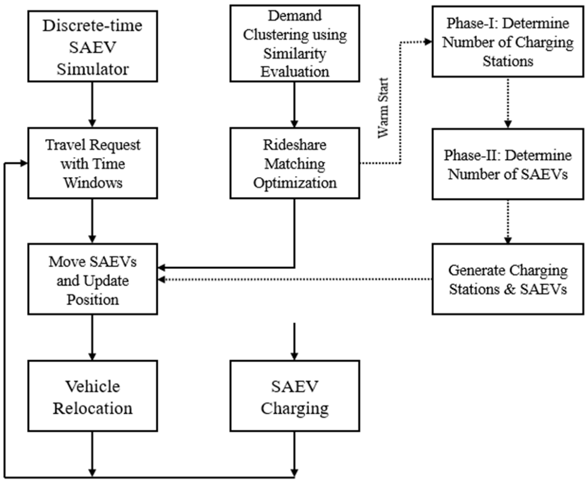


FIGURE 7. Simulation model with rideshare matching (Farhan & Chen, 2018) [29].

In [29], a fleet of shared autonomous electric vehicles (SAEVs) was observed utilizing a stand-alone agent-based simulation to model the benefits ridesharing as a concept offers compared to ride-hailing services in autonomous electric vehicles. The study utilizes a 100-mile by 100-mile radius to model special density patterns of a population in Austin Texas. The methodology applied for the research involved a 3-step analysis which considers discrete-time SAEV simulation model, clustering using similarity evaluation and rideshare matching optimization model. Fig. 7 shows a framework for Discrete-time SAEV Simulation Model with rideshare matching. The first step involves a pixilation of a predefined travel region using a discrete-time rule-based simulation model. Several cells are established to represent passenger trips at each 5-min time step. Computation of total distance travelled was captured as Manhattan distance which represents the sum of the absolute difference between two vectors. To simulate realistic situational analysis, traffic congestion in this case is modeled as a function of time-of-day. The current vehicle state is updated at each time step to any of the following pre-specified states "in use", "available", "relocating", or "charging". The simulated vehicles can strategically relocate when not in use to reduce wait times for potential travelers, and recharge batteries if needed. with respect to real world peak traffic timing obtainable around cities. Vehicle status is represented by "in use", "available", "relocating", or "charging" depending on the time-step variable within the simulation giving them the opportunity to move from one point to the next while out of use hence reducing wait times and gaining recharge during these hiatus periods. The second step involves decomposition of the ridesharing problem into several smaller problem units and further partitioning of the search space reducing problem solving efforts into bit-sized considerations. Step III involves selection of optimal routes for passenger journeys. These selections are made with the constraints of permissible time intervals and fixed capacity in view and modelled as a Capacitated Vehicle Routing Problem with Time Windows (CVRPTW) for each traveler. The study established that greater than 50% of Vehicle Miles Travelled (VMT) took place in a ridesharing for vehicles with a four-passenger sitting capacity. This is complementary to the deduced average of 34.7% representing overall commuters that participated in ridesharing. The results demonstrated a possibility of financial benefits ranging from $1.34 million to $1.52 million obtainable from different ridesharing configurations.

The authors in [30] studied the application of Universal Design (UD) and the possibilities it offers in shaping the future of urban public transport in Indonesia. In this research, the application of UD was considered in the development of electrically powered autonomous vehicles (AV) to be applied in the sharing economy concept. The concept is made appealing by the possibility of realization of transport systems which offer ecofriendly and user-friendly advantages in their user environments. Ridesharing in this analysis, was observed to enhance consumption patterns by eliminating occurrences of over-consumption and underutilization of assets. The authors deployed a framework premised on the concept of design thinking utilized to develop the context of the research. The conceptual framework includes empathize, define, ideate, prototyping and test steps. Different phases of the design thinking framework establish necessary background for subsequent phase assessments to be executed. The empathize phase displays shadowing properties and universal design principles which generate relevant input for the define phase. Also, the use of sketches and 3D representations in the ideate phase promote visualization of how qualitative and quantitative testing may be executed in future prototyping.

The authors identified a seven-principles approach the concept of UD utilizes to gain its relevance. These include the requirement for UD usage to offer equitable representation, flexibility, simple and intuitive applications, perceptible information, margin for error, low physical effort, and finally adequate properties for approach and use. The first requirement for equitable use permits all users including those with physical disabilities interface with products just as easily as other users would. The second requirement of flexibility relates to the requirement for users with differing needs and abilities to find applications within their capacities. The requirement for simplicity and intuitive use means the designs obtainable from the process must be comprehensible across different backgrounds irrespective of users, experience levels, knowledge bases, language, skills, and concentration levels. The principle of perceptible information means UD will represent with clarity, the information required by the user given differing situational variables, levels of conditioning, and user's sensory abilities. The requirement for tolerance for errors means reduction in risk probability and possibility of losses and damage resulting from accidents. The sixth principle requires low physical effort representing a demand for increased efficiency of process outputs and less likelihood for instances of failure. Finally, the need for size and space involves the reasonable availability of capacity for users depending on their differing range of body sizes, posture, or degree of mobility user possesses.

Smartphone application design platforms were used to demonstrate the concept of UD and sharing economy. Also deployed to demonstrate and conceptualize UD are Autonomous Vehicle fleets with necessary support infrastructure customized for AV operation. Within the properties of Universal Design exist potential for deployment of the concept in public transportation systems of the future in urban areas with concentrations of Autonomous vehicles. This research creates an awareness of possibilities in sharing economy systems for establishment of sustainable transportation networks. When these concepts are deployed utilizing universal design, a situation is created where resultant systems cater to a wider demography of users seeking a wide range of experiences.

The authors in [31] addressed the issues of uncertainty in closing hours for different business organizations capable of preventing commuters from getting involved in ridesharing. The research focused on development of an evening commute bottleneck models which considers the variables of uncertainty in work end times and choice of transportation mode with a view to establish an equilibrium round-trip commute. The impact of autonomous vehicles on the overall balance is assessed and compared with regular vehicle options. Two scenarios were highlighted as influences for commuters in regular vehicle ride sharing. The first instance considers single drivers embarking on trips while the second case study involves commuters in ridesharing for commutes to and from work locations. Each case was then considered from a mode choice equilibrium viewpoint to identify properties inherent in the differing modes. The authors considered the complexities created by the fact that rides involved jointly in morning ridesharing arrangements are likely to experience separate return trips as differing work close times will become an influence on pairing options and the potential for deployed Autonomous vehicles to provide solutions in such situations. Based on the premise that individuals sharing rides in morning commutes share similar home and work locations it is then assumed that there is upset in cost structure arising from differing work schedules. The requirement for repositioning of an additional autonomous vehicle to cater to different pick-up times will result in two round trips. This is equivalent to the total cost implication for a pair of ridesharing partners eliminating the potential for additional cost obtainable in separate roundtrips for single riders.

E. TAKE-HOME MESSAGE SUMMARY FOR RIDESHARING MODELS AND ARCHITECTURES IN TRANSPORTATION

The survey works in this section have uncovered the following points and take-home messages for ridesharing models and architectures in transportation:

- The sub-section has shown that reasonable research efforts have been invested to understand the general scaling behaviour request patterns of ridesharing and its dependence on the street network topological properties of the ride network. Such an understanding is necessary to effectively design and compare dispatching strategies, examine and improve network performance, and determine the optimal flow pattern and to adequately predict the potential benefit of ridesharing.
- Studies on taxi models for ridesharing are largely on designing optimal scheduling, transfer mechanism, and

on Dial-a-Ride Problem (DARP) which have been extensively studied for static scenarios in which all riders' requests are known in advance. However, there have been fewer works reported for dynamic scenarios (dynamic DARP), in which rider requests are calculated and generated on-the-fly. More studies are required to examine the factors that affect the dynamic nature of taxi ridesharing models and architecture.

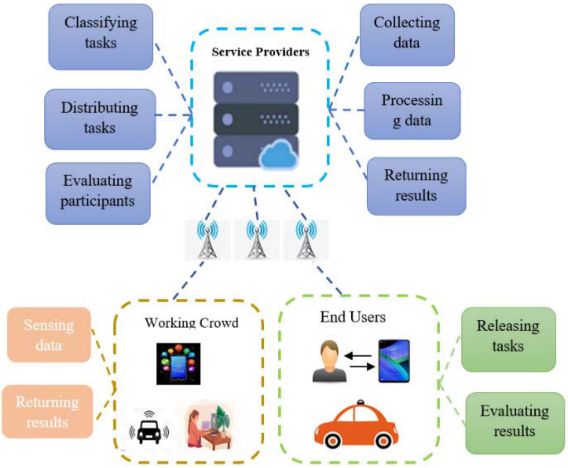
- Bus ridesharing has been proposed to satisfy the recurring, long-distance and low-cost associated with taxi ridesharing. Studies in this area have focused on querying and ascertaining global shortest path on road networks, optimizing ride-matching services, maximizing the success rate, and implementing dynamic bus routing (DBR).
- Recent advances in autonomous driving technology and autonomous vehicles have shown the potential to evolve traditional carpooling services into autonomous ridesharing systems (ARS). ARS promises a transportation system that is beneficial and user friendly to the society with many environmental benefits including lower accident rates, lower energy consumption and pollutant emission, and reduced land use for parking. Because AVs can reposition themselves, the negative impact of activity duration uncertainty on ridesharing could be mitigated [31]. However, developing ridesharing models that achieve optimal matching rates and optimized dynamic routing, and understanding the extent to which uncoordinated behaviour on ridesharing participation decreases the efficiency of ARS remains an open research challenge.

III. CROWDSOURCING MODELS AND ARCHITECTURES IN TRANSPORTATION

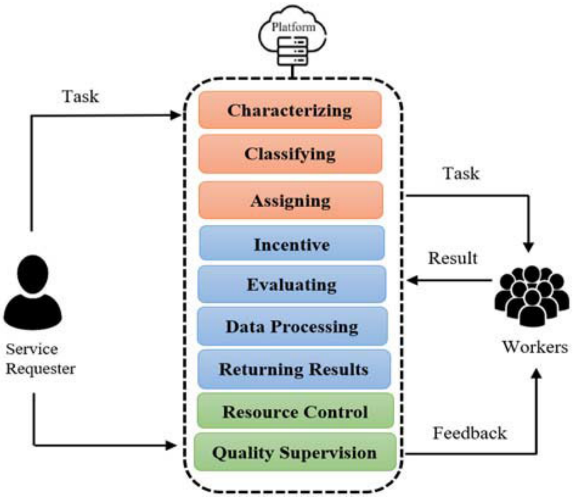
Transportation is an integral driving factors for the source-economic prosperity of communities and also for the mental and emotional wellbeing of citizens (plays an essential role in day-to-day pursuits of the citizens). Because of the growing population and urbanization, there is a significant increase in demand for safe and efficient transportation system. Efficient acquisition and analysis of data pertaining to transportation can promote the identification of obscure features and patterns that can enhance the efficient utilization of constrained transportation facilities to meet the growing populations [32]. Crowdsourcing provides a process of data collection from a large number of people who participate in the task of contributing data about a specific scenario to solve a problem. With the proliferation of smart phones equipped with diverse kinds of sensors, participants in a crowd sourcing task can utilize their mobile phones to collect and contribute data in real time [33]. Table 2 shows a summary of ridesharing models and architectures in transportation discussed in the sub-section.

A. CROWDSOURCING MODELS AND ARCHITECTURES

Fig. 8 shows a general architecture for crowdsourcing and the participating entities. Fig. 8(a) and 8(b) shows the crowdsourcing architecture and crowdsourcing process respectively. Basically, a general crowdsourcing architecture or system would have three components or entities which collaborate and work together: (1) Service providers; (2) End users; and (3) Working crowds. Service providers receive the requests, divides it into smaller tasks and distributes the tasks to participants or workers to complete the tasks. Upon receiving a task from a service requester, the platform will characterize, classify, and assign the task to appropriate participants or workers. The service provider may offer incentives to participants in different forms. The platform may evaluate the performance and returned quality from workers. The data is then processed by the platform and the results are then returned to the service requesters. Comments or feedbacks may be provided by the service requesters and then given to the workers. The crowdsourcing platforms have the responsibilities for the ensuring of quality and resource control. As shown in Fig. 8, the major components in a crowdsourcing architecture are: (1) Task assignment and management; (2) Data collection and information processing; (3) Worker and participant evaluation; (4) Development of



(a) Crowdsourcing architecture.



(b). Crowdsourcing process.

FIGURE 8. **General architecture and process for crowdsourcing.**

TABLE 2. Summary of crowdsourcing models and architectures in transportation.

Focus area	Work contributions	References
Vehicular-based Crowdsourcing and Vehicle Social Networks	Vehicle-based crowdsourcing system in a smart city	[38]
	Radio units (RUs) mounted on parked vehicles in smart city environment	[39]
	Cooperative data forwarding (CDF) architecture for vehicle social networks	[40]
	Spatial vehicular crowdsourcing scheme for opportunistic collection of data in smart city	[41]
Crowdsourcing and Public Transportation	Communication Assisted Road Transportation (CARTS) system architecture	[48]
	Crowdsourcing-based public transport mode detection technique using smartphone	[50]
	Named Data Networking (NDN) for crowdsourcing transportation information services	[52]
Crowdsourcing Traffic Flow Estimation and Accident Prevention	Crowdsourcing data model for real-time accident analysis	[59]
	Crowdsourcing-based platform for collecting and processing near miss incident data (SimRa)	[60]
	Real-time framework to utilize Twitter data to detect incidents in transportation network	[61]
	System to predict short-term condition of urban road network using social media data	[62]
Crowdsourcing for ITS	CrowdITS framework which utilizes smartphones to gather human input and sensory data	[65]
	CrowdNavi navigation architecture which utilizes driving information from users to determine patterns in driving activities	[66]
	System architecture for real-time navigation framework using data from road users, infrastructure-based and on-board vehicle sensors	[71]
	Spatial crowdsourcing for 3D map generation	[73]
Crowdsourcing for Goods Distribution	Crowdsourcing for urban freight transportation	[78], [79]
	Simulation framework and probabilistic modelling for making freight trucks smart	[82]

incentive mechanisms; and (5) Development of strategies for cost reduction.

An example of a crowdsourcing model and architecture for smart cities can be found in [34]. The authors proposed a crowdsourcing-based platform termed as CrowdService which is a platform to allow multiple players to collaboratively produce more services. Fig. 9 gives an overview of CrowdService and its major components. Their work involves collection and integration of open Internet resources and smart city information resources, for example, data extracted from government IS, into their platform which is open APIs. CrowdService provides a software engineering

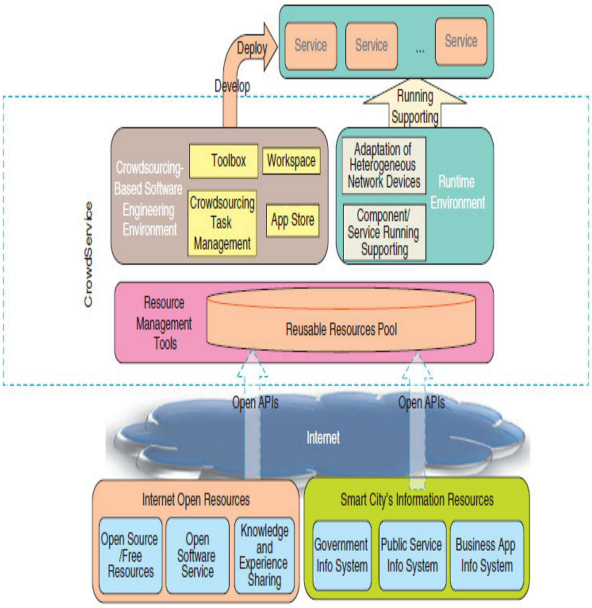


FIGURE 9. **Crowdsourcing architecture for smart cities [34].**

environment which includes the major functionalities of: (1) Crowdsourcing task management to support the crowdsourcing life cycle process; (2) Toolbox and work space to provide development tools, e.g., requirement modeling, process definition, service composition; and (3) Service store for providing support for classification, recommendation tasks, etc. CrowdService has been deployed in several cities in China to support human-centric applications and services.

B. VEHICULAR-BASED CROWDSOURCING AND VEHICLE SOCIAL NETWORKS

This subsection discusses the new paradigms for utilization of vehicular-based crowdsourcing and vehicle social networks for smart city applications. Vehicle-based crowdsourcing is emerging as a promising paradigm for outsourcing computationally heavy activities to vehicles by leveraging their on-board capabilities. Vehicles are likely to be equipped with sophisticated processing capabilities, and communication and sensing abilities for the foreseeable future as they become more connected and autonomous. As a result, if data can be properly gathered and managed these onboard resources can be used for processing, communication and sensing services in a smart–city context without incurring extra deployment costs. It will reduce the pressure on our current infrastructures and also stimulate the development of new smart-city applications. Despite the fact that several works use this concept to engage vehicles to accomplish jobs, putting it into practice is very challenging without a robust incentive design. This is due to vehicle owners reluctance to voluntarily share their onboard resources due to concerns about energy usage in batteries, leaks in location privacy etc., [35], [36], [37]. These and many other challenges have motivated research in this domain.

The authors in Chen et al. [38] constructed a delay-aware incentive strategy for motivating vehicles to participate in crowdsourcing system as reverse auction. The strategy allows participating vehicles to bid for the task of their choice by submitting both their bidding prices and the estimated time of completion (ETC). The suggested approach is modeled as a non- monotone sub-modular maximization problem with a knapsack constraint to maximize the utility of service requesters under a budget constraint. The authors further presented an approximation method for selecting and determine payment for bids because of the NP-hardness of the given problem, which ensures truthfulness, feasibility budgeting, profitability, personal reasonableness and processing efficiency. The results of their simulation experiment demonstrated that the suggested incentives mechanism is very effective. In this work, the authors proposed a reward system for vehicular crowdsourcing that takes into consideration the vehicles uncertain travel time. Based on a discrete-time traffic model, the authors deduced a compliant formula for the probability distribution of task delay considering the stochastic behavior of traffic conditions. Using a reverse auction framework, a service requester's utility is modeled as a function of uncertain job delay and obtained payment. The designee mechanism is further modeled as a non–monotone sub-modular maximization problem with a knapsack constraint to optimize requester's utility while staying within a budget. The author further constructed a truthful budgeted utility maximization auction (TBUMA) using the formulation. The effectiveness of the suggested reward mechanism was demonstrated using comprehensive trace- based simulations.

Nakayama et al. [39] suggested the concept of small cells consisting of radio units (RUs) mounted on parked vehicles in the case of a smart city environment. The small cells are activated using traffic demand in close proximity via road side units (RSUs). The suggested concept is based on the relationship between population distribution and parking lot occupancy rate, which can significantly increase user through put with a modest number of RVs. Experimental results showed that when a high capacity back/front haul link is available, locating small cell access points close to the traffic hotspot can improve performance throughput.

Vehicle social networks (VSNs) present a new type of communication that allows passengers to communicate and socializes with one another while on transit. With the development and integration of intelligent onboard devices, with enhanced communication and processing abilities, passengers can create and exchange contents of common interest within online communities while in transit. Crowdsourced data gathered from onboard devices and passengers can help offer meaningful insights into traffic condition, road accident etc., and enables passengers to make informed decisions. However, a dedicated or end-to-end communication line may not exist among passengers in VSNs because of extremely dynamic network structure, short- term communication connection and variation in vehicular density. As a result, passengers communicate opportunity with one another and data is transferred in a store–carry-and-forward method. Several research efforts have been made to address these challenges confronting VSNs.

Rahim et al. [40] designed a cooperative data forwarding (CDF) architecture for formulating data in socially selfish vehicular Networks (VSNs). Their architecture is designed to utilize the trust and cooperative reputation of middle without requiring credit control or distribution from a centralized or third party. Their CDF model compels the selfish node to improve its cooperative behaviors in order to gain a high reputation among network nodes and have its messages replicated. The CDF mechanism was evaluated with real-world traffic data and the results of the experiment revealed that the suggested mechanism successfully encouraged selfish nodes to join in data forwarding and improves network in respect to end-to-end delay and data delivery ration, which can greatly improve crowd-sourcing data collection in VSNs.

Leveraging vehicular ad hoc communications, Urra and Ilarri [41] proposed a spatial crowdsourcing scheme/method for the opportunistic collection of data within an area of interest in a smart city. In such a circumstance the system describes a strategy that uses mobile agent technology to achieve distributed data gathering and querying among vehicle. The proposal was subjected to extensive simulations which demonstrated the viability of the approach.

C. CROWDSOURCING AND PUBLIC TRANSPORTATION

In today's urban environment, public transportation is a central facilitator of mobility. While taking public transportation is ideal, it is confronted and hampered by two key main factors: Road traffic congestion (creating uncertainty in when individual units arrive or depart) and overcrowding [42]. Traffic congestion is a critical challenge in comparatively big cities especially during peak periods. Many researchers have attributed this problem to inadequate funding or unreasonable allocation of resources, bureaucracy, limited land space to accommodate a traffic volume, rapid increase in population as well as increased number of individual vehicles. Relevant experts and stakeholders in this domain are still grappling with how to alleviate and eliminate the increasingly severe urban traffic situations. Quality of service is defined by public transportation operatives and providers of services using several quantitative measures that include travel time, travel cost, number of passengers served, timely performance, and so on, together with qualitative measures which include passengers experience [43]. Developing a contemporary, efficient and workable transportation services typically rely on the obtainability and conveyance of relevant and real time data for both the transport operators and passengers. Real time public transportation information system is considered a step towards enhancing passenger's transition experience. Several studies show that simply provisioning the right information in real time can impact passengers experience positively, enabling them to make more informed decisions. It also enables transportation service providers plan for the short-term scale (such as notifying passengers of the location of the next bus) and long-term scale (such as determining the number of buses that will run a particular route) services [44].

With Intelligent Transportation System (ITS) a number of techniques have been proposed that utilizes sensors and wireless communication networks to minimize road traffic congestion. However, a host of these techniques such as inductive loops, imaging-based system, light detection and ranging (LIDAR) systems, etc. are expensive to implement. The authors also make some degree of assumptions about orderliness, lane system and low vehicle variableness which makes them unsuitable for the chaotic conditions of roads found in most cities especially in developing cities [45].

Crowdsourcing can be viewed as a contemporary paradigm for collecting, augmenting and making real-time data available to passengers, service providers and other stakeholders, through mobile application or passenger information system. It can also be utilized to validate the accuracy of such systems and obtain feedback on their performance. With the increased adoption of smart phones and the advancement in the technology of recent smart phones, new possibilities are created for various types of crowdsourcing tasks. Recent smart phones are equipped with several varieties of functionalities and sensors which includes GPS, magnetometer, accelerometer, gyroscope, temperature sensor, microphone and so on. For example, position tracking on a map can be realized using the GPS, and the direction of a movement of a phone can be detected using the accelerometer etc. With smart phones, people participate in mobile crowdsourcing to complete various task such as data collection. data verification, etc. These tasks are made easier to complete with the help of mobile crowdsourcing thereby enabling its utilization by researchers in a variety of fields such as location-based services, transportation, disaster management, etc [46], [47].

Patil et al. [48] proposed a communication framework named Communication Assisted Road Transportation System (CARTS) which can assist in easing congestion and facilitating easier use of public transportation system for commuters. Their goal is to deliver real time and relevant information about individual transportation unit current location, crowding and road utilization, to enable passengers plan their journeys, allow authorities dynamically distribute buses to precise route as well as ensure that individual vehicle owners choose when and which route to commute. The framework uses an Android-based crowdsourcing application for gathering and dissemination of timely information about current location and crowding to commuters (The CARTS framework gathers information using a crowdsourcing smartphone App and on-road sensors in a content-centric manner). Passengers can query the system to obtain information about buses plying to a desired destination from a particular time. They can also subscribe to receiving information about buses plying a particular route at a particular time. On-road sensors (e.g., Wireless-Across-Road, Video Feed etc.) are utilized to gather road utilization information and deliver it. Rana et al. [49]

employed crowdsourcing for smart phones to construct a public transport management framework to enable commuters locate nearby public transportation such as train, bus, etc. to their targeted destination. The system uses the smartphone GPS to gather location information. The system allows commuters to supply their origin and destination location when searching for accessible close by public transports, which it then uses to track information about the public transportation applying mobile crowdsourcing. Commuters can be able to see the precise location of the transportation unit and arrive at the stop without any waste of time. The experiment of the system was conducted in the city of Dhaka with 300 public transportation information for a number of regions. The system proved to assist the commuters in reducing mental stress while also increasing security.

Nirmal et al. [50] designed crowdsourcing-based public transport mode detection technique using the smartphone GPS and accelerometer data and machine learning algorithms. The authors developed and utilized a mobile application to collect data and disseminate real-time location of identified modes of public transportation to users. The technique employed the Couchbase DB together with the sync gateway to effectively convey real-time data gathered with the mobile application to the cloud where a machine learning model is applied to the data to classify the device's transportation mode. The results are further utilized to update a database that caches each devices current mode. To choose the best learning algorithm as well as segment size, the data cached in the database was first segmented into three datasets (1 minute, 2 minutes and 3 minutes segments). Classification, binary classification and multi-class classification was performed using five learning algorithms and their performance was evaluated against accuracy, precision and recall as metrics. The results showed that the models performance increased as the segment size increases.

Kong et al. [51] designed a framework for smart city shared bus profiling based on varying mobile crowdsourced data. The authors collected commuters order data as well as driver GPS data using Future Fleet, a shared bus application (APP) for mobile phones. Second, once the shared bus has been obtained, the critical challenge is determining a strategy for studying and comprehending the travel needs of residents from various perspective, and then constructing a precise commuter profile. In order to address the issue, the authors constructed a travel profiling (TP) method for determining resident travel, which they refined into loss tolerance, delay tolerance, seat utilization rate (SUR), waiting time, and journey time. Finally, a multi-constraint evolution algorithm (MCEA) was constructed to improve the TP-based routes. TR Profiling performed exceptionally well in terms of meeting the needs of commuters according to the experimental results.

Since the services of real-time ride sharing or simply ride sourcing like Lyft, Uber and Grab emerged, the public transportation experience has been transformed with regard to popularity and use among riders. These fairly recent ridesharing services rely heavily on information, which is dependent on the transportation provider continuous internet access availability. Usually, the essence of conveying relevant and real-time information to the riding public is to allow them make convenient and efficient decisions of how (what transportation mode to use), when and where a ride can begin, progress and end. However, the supportive information services that appears to be a key characteristic of contemporary public transportation are difficult to deliver in regions where telecommunications services or access to the internet are either inadequate or prohibitively expensive. This situation is exacerbating considering the fact that these locations (e.g., rural area or low-income urban or suburban areas) are areas in urgent need of modernized public transportation. Although transportation providers may have the ability to create and acquire the required information infrastructure internally, and although their potential riders may have devices like mobile phones to gain access to information, insufficient access infrastructure in the external environment of the transportation provider building as well as commercial mobile internet service cost impede real-time transportation information accessibility and dissemination. This problem has attracted the attention of researchers in this domain.

Dureza et al. [52] investigated the utilization of Named Data Networking (NDN) for the purpose of crowdsourcing transportation information services, which allows for accurate matching of information needs among riders and transportation providers. The authors viewed the primary dealing among riders and transportation providers to imply interest marching, opining that only when there is an inferred or declared matching of interests relating to time, route, proximity, location, pricing availability, or other requirements will a ride be possible. The proposed scheme also considered communication as more of about matching data and less of the ability to find and connect end-host, particularly considering the difficulties of having extremely mobile and sporadically connected customers. The nduSIM was employed for the simulation of the scheme based on the campus of University of the Philippines, and it tracked public transit vehicle known as Jeepneys. The open-source traffic simulator Simulation of Urban Mobility (SUMO) was utilized to produce mobility files which the built-in tracers in nduSIM were utilized to evaluate latency as well as the percentage of satisfied interest. The simulations results demonstrated a good performance in terms of Query Hit compared with typical IP infrastructure-based communication, but at a cost of increased latencies.

D. CROWDSOURCING TRAFFIC FLOW ESTIMATION AND ACCIDENT PREVENTION

Traffic volume represents an inherent feature of transportation systems that is critical for a wide range of applications. Network-wide traffic volume remains an essential ingredient for finding solutions to problems associated to city transportation in the area of traffic planning, for instance calculating the volume-capacity ratio, estimating the origin-destination (OD) matrix, and identifying bottleneck highways [53]. It can also be employed by the transportation managers to implement a dynamic traffic control program and respond rapidly to non-recurring traffic congestion [54]. Furthermore, such information may be used to evaluate pollutants emissions notably a critical challenge for inventories of mobile emission in the environmental field [55]. Camera-based volume detectors have been extensively used in recent years for violations detection and traffic situation monitoring. These smart cameras calculate the total traffic volume by distinguishing the license plates of individual vehicle. Despite their increasing use, volume detectors still have insufficient coverage in metropolitan areas due to the high cost of installation and maintenance. The data collected by smart camera from a small number of road segments cannot exactly be used to generate network-wide traffic information. However previously collected data of the entire road segments could be utilized for temporary short-term traffic prediction, but is insufficient for the estimation problem of network-wide traffic flow.

Crowdsourced data such as crowdsourcing floating car data gathered from navigation apps (such as Google Maps, AMAP, etc.) or ridesharing platforms (such as Uber, Lyft, etc.) have a broad range of coverage and are becoming more common in the field of transportation. After the map-matching preprocess, crowdsourced floating car data can be used to generate network-wide traffic speeds. Because speed patterns typically harmonize with volume patterns, common features among road sections could be deduced in relation to the speed pattern, which can subsequently be used for road segments volume estimation without the use of detectors [56], [57]. With crowdsourcing floating car data, Zhang et al. [57] proposed an approach that integrates spatial affinity correlations and temporal continuity characteristics to form a geometric matrix factorization model for estimating network-wide traffic flow. The authors formulated the proposed model as a quadratic programming and solved it using the alternating direction method of multipliers (ADMM) algorithm. The proposed approach is validated using real-time as well as synthetic datasets and the results showed it performed better than different benchmark models. Furthermore, the spatial smoothing index designed by the authors to assess the complexity of volume estimation per road segment is immensely correlated to the accuracy of the estimation.

Traffic accidents are common occurrences which may be as a result of bad weather, bad driving behavior, etc. and at such may cause congestion to a certain degree in a section of the road network or possibly produce a chain of failure in the whole network whenever the occurrence coincides with a traffic jam. This accident-induced congestion is regarded as a non-recurrent congestion. One significant step to addressing this mobility problem is to precisely predict Traffic Accidents Post-Impact (TAPI) to guide road users and ensure efficient management of integrated transportation systems. One essential element to realizing this is the real time spontaneous access to accident information as well as the surrounding traffic situations [58]. Using crowdsourcing data, Lin and Li, [59] studied the strategies for predicting the intricate nature of traffic flow evolution following traffic accidents. According to the obtainable data, the authors classified the traffic situation into four levels based on the congestion delay index which includes uncongested, slow moving, congested and extremely congested. Based on the occurrences, each occurrence level, four categories of accidents are established. The author designed a hierarchical method with embedded machine learning algorithms (Random Forest (RF)), Support Vector Machine (SVM) and Neural Network (NN) which detects the most congested level and predicts the duration of each level successively. The validation of the suggested model using 2017 accident data in Beijing, China showed that the suggested method is effective. The study demonstrates that crowdsourcing data could be effectively utilized by the suggested model for real-time accident analysis.

Karakaya et al. [60] designed a crowdsourcing-based platform for collecting and processing cyclist routes and near miss incident data named SimRa. The platform comprises three major modules: data acquisition, storage, and analysis modules. For the data acquisition module, the authors design a mobile application which participating cyclists in the crowdsourcing task install in their smartphones. The cyclists start the application which enables during a ride, the platform to track smartphones GPS, accelerometer and gyroscope sensors at different rate per minute, and records riders' current location and radius, sudden peak and device orientation data at different rate settings. Once the cyclist ends the recording after a ride, the recorded data is analyzed to detect incidents. In order to accurately detect incidents, the authors designed an incident detection heuristic based on the idea that incidents frequently occur when there are sudden spikes in acceleration. To separate incidents and bad road conditions, the heuristic partitioned the time series of acceleration into buckets. The minimum and maximum values of every dimension in every bucket is then determined and the difference between the two is computed. Furthermore, the six most significant differences in all buckets are categorized as possible incidents to allow for distinguishing between high acceleration values caused by bad road conditions and incidents. Practically, the heuristic performs better on cyclists who ride in a "relaxed" manner.

However, it frequently detects either traffic light, significant bumps or accidents but not incidents for bikers with a "fast" cycling style. It is also unable to identify close passes or similar situations that do not occur when there is spike in acceleration.

Aside from the limitation of the heuristic which can also be improved, there are some types of incidents that cannot be detected automatically from the sensor data alone. SimRa therefore request the cyclists to modify pre-detected collection of incidents (namely, add false negatives while disregarding false positives) and mark as well as comment the accurate collection of incidents. Afterwards, the cyclists trigger the upload of the ride data to the backend which is authenticated to prevent automated attacks. The ride data (route and incident data) and profile data (demographic and grouped ride statistics for each cyclist) are stored per region to allow for data from different regions to be individually analyzed. SimRa provides two data analysis options; exploratory and confirmatory data analysis. The authors created a web application for expository data analysis that enable users examine the acquired data interactively using visual analysis. The application displays rides and incidents as lines and markers respectively on a map and provides a collection of filters that users could utilize to filter rides as well as incidents in reference to time and ride data attribute. Users will be able to discover incident hotspots using the online application by first checking for incident clusters and thereafter match them to various rides on specific roadway section or crossroad. In the confirmatory data analysis, the authors first translate the acquired data to a format that enables the mapping of incidents to crossroads or street sections, and constructed a graph model which conceptualize a map where the nodes represent crossroads, and the edges constitute street sections in the middle of crossroads. With the model, a score that portrays the possible degree of danger in a specific street section or crossroad can be computed. SimRa was deployed in Augsburg, Berlin, Stuttgart, Pforzheim, Bochum (all Germany) and Bern, Switzerland and the results of experiments demonstrated that SimRa produced the expected results.

Based on mobile crowdsourcing abilities, further approaches for measuring and predicting traffic congestion have been developed. Jones et al. [61] presented a framework that utilizes real-time Twitter data to detect incidents in real-time in a transportation network in the UK. The framework employed Natural Language Processing (NLP) techniques for data retrieval and processing, and Support Vector Machine (SVM) for classifying text. The system proved potent in predicting traffic congestion while the proposed approach achieved 88.27% accuracy in detecting traffic related tweets. Yan and Yu [62] constructed a system that applied social media data and improved SVM to predict short-term condition of urban road network.

E. CROWDSOURCING FOR ITS

ITS (intelligent transportation system) employs a variety of technologies for sensing and communication to aid transportation authorities as well as vehicle operators in making informed decisions while also providing a pleasurable and risk-free driving experience. Effective and efficient data collection and dissemination are critical for the successful operation of applications for ITS. The present and anticipated future surge in mobile and embedded technologies offer an extraordinary possibility for crowdsourcing platforms to collect more meaningful in order to make data-driven system level decisions. Researchers however have in recent times developed data collection and dispersion framework for ITS that includes vehicular social network (VSN), roadside units (RSU) as well as aerial vehicles (UAV) which aim to use present and future extensive broadband internet connectivity for data-driven transportation system improvement. Crowdsourcing based on ITS that leverages the forenamed frameworks as well as its thick connectivity provides the potential to generate a tremendous inflow of new data to work with for ITS operators [63], [64]. The widespread adoption of smartphone technology has resulted in an ever-expanding collection of possible crowdsourcing opportunities in a variety of disciplines such as transportation. The use of a mobile platform (such as smartphone) by workers to perform an assigned task is referred to as mobile crowdsourcing. An example of contemporary mobile crowdsourcing utilized in transportation is Uber and Waze.

Researchers have developed and utilized mobile crowdsourcing platforms for several ITS application. Ali et al. [65] proposed CrowdITS, a framework that utilizes a smartphone to gather human input as well as open sensory data and communicate them to a processing server. The architecture of CrowdITS consists of three main parts – Crowdsensing and interface, information processing, and localized device message. The interface part may be used in an interactive or pervasive mode or both. With the interactive, user can use two methods to input incidents. First, a list of incidents is provided in an interactive screen for users to choose from, and because it is a single touch-interface, it prevents substantial drivers' interference.

Second, preconfigured sets of commands are provided for use with voice commands. The users can define the incident, its severity, the estimated timeout as well as additional metadata. Incidents gathered with any of the input method is automatically time-stamped and geo-located.

The recorded time-stamp is utilized to separate out irrelevant items and set an expiry time for them, while the geo-location is transformed into a geo-hash and utilized to organize incidents and forward notifications to users' mobile devices. Mobile phones in the pervasive mode input sensory data (such as GPS) on regular basis which can be utilized to assess the speed and direction of vehicles resulting in traffic congestion. The information processing module offers three major service - retrieval and storage of information, registration and authentication, and localized messaging to mobile devices. To deal with the number of data sources and volumes, the author constructed a plugin- based scheme which the centralized processing server leverages for scalable and extendable use of the multiple data sources and volumes accessible for ITS. In the localized messaging module, the data gathered from all sources are aggregated to create significant incidents for any geo-hash grid(s). The users register for prospective notifications by subscribing to their own interested grid(s). The authors incorporated the CrowdITS with Cloud to Device Messaging (C2DM) service to pull notifications to mobile devices. CrowdITS is implemented on Android as well as iPhone platform for congestion free re-routing application.

Fan et al. [66] constructed a navigation architecture named CrowdNavi, which utilizes driving information crowdsourced from users to determine patterns in their local driving activities and suggest the best local path for them to take, particularly, the last mile puzzle faced by drivers close to their destination where navigation services such as Google Maps offer less thorough guideline or just fails. The system provides a comprehensive set of algorithms for clustering landmarks generated from driver trajectories to detect entry landmarks around the final mile, and estimate the landmark options. The optimum route through the landmarks is then located for the final mile using an efficient navigation algorithm. CrowdNavi also presents a security strategy for detecting the attacker's simulated and malicious data. CrowdNavi is implemented on Android mobile operating system and the result, after evaluating its performance revealed that it outperforms other navigation systems in directing drivers in the final mile to their destination.

A class of crowdsourcing requires the physical presence of workers in a particular location while fulfilling the job. This is referred to as spatial crowdsourcing. The major aspect of spatial crowdsourcing remains the existence of spatial jobs that demand the crowds' physical presence at a specific position to perform the task [67]. The computing and connectivity power delivered by PMDs are utilised wherever the user takes the device to supposing the network connection is strong enough. In fact, smart phone flexibility, together with their broad connectivity makes them an ideal platform for spatial crowdsourcing jobs. Although mobile devices constitute the dominant channel for spatial crowdsourcing, however, the advancement in embedded IoT technology, particularly in automobiles, enables the development of new spatial crowdsourcing systems which operate passively rather than actively as in mobile crowdsourcing jobs [68], [69]. Roman et al. [70] proposed a mobile system to detect on-street parking space. The system measures the distance between the vehicle and the road using ultrasonic sensors fitted on the car's side. The system employs a supervised learning algorithm to analyze the form of the sonar trace in order to distinguish between parked vehicles and clutter on the road. Preprocessed sensed data, specifically the annotated parked cars, empty space, vehicle speed, GPS positions, as well as timestamps are sent to a central server and utilized to generate a parking occupancy map. The system also incorporated a map matching (MM) mechanism to compensate for any error in the GPS position information. The system updates the parking availability information any time a car equipped with sensor discovers a space. The availability of parking spaces is communicated to users through a Web portal or mobile app. Drivers can utilize such information to discover Street parking, saving time and energy spent looking for a parking space and also for making informed navigation decisions.

With crowdsourced data generated from road users, infrastructure-based and on-board vehicle sensors, Wan et al. [71] designed a system to evaluate the status of traffic networks and optimize vehicle navigation in metropolitan environments. Their work focused on creating real-time route planning algorithms that use the frequent input of crowdsourced data to calculate in real-time, the fastest single and many paths for vehicles to get to their destination. First, the routing problem is formulated as integer linear programs (ILPs) and solved using iterative approaches levels putting into consideration, the update in the traffic data. Thereafter, the authors introduced algorithms that leverage on lower complexity sub-optimal graph to solve the routing problems in real-time. The proposed framework updates the vehicle path after a set length of time, which is defined using timely correlated data unlike conventional navigation solutions. Experimental results revealed the superiority of the proposed framework over conventional solutions in terms of avoiding congested streets as well as choosing less congested roads. This system will assist delivery vehicles drivers to discover the shortest path to numerous destinations for dropping off products before reverting to the commencing points.

Spatial crowdsourcing could also be leveraged for several other ITS application such as constructing panoramic tours [72] and autonomous vehicles 3D map generation [73]. Smart vehicles' embedded sensors may be leveraged by ITS applications for passive data collection while they are in operation, which is then transmitted to a central system for analysis and utilization. Passive data collection jobs can be used for real-time vehicle fleets tracking, automated lane imaging, autonomous vehicle navigation, etc. The work of Kumar et al. [74] presented a technique based on RFID communication for tracking public transportation vehicles in real-time. This system is considered economical and cost effective for developing countries who may not be able to implement more expensive GPS based techniques. Tang et al., [75] constructed a system that collects lane-based road information using crowdsourcing. With the use of crowdsourced data gathered by vehicles, the system can derive the exact lane organisation of roads automatically. The system first filters the raw trajectories to generate extremely accurate GPS data based on the expanding clustering of regions and past experience. Second, the system employed an improved controlled Gaussian mixture model to determine the number, as well as placement of traffic lanes. The system was experimented in Wuhan, China using taxi GPS trajectories and the result revealed that the suggested system precisely measured and displayed road network, capturing traffic lanes number as well as positions as compared to the situations of human interpretation and satellite image.

F. CROWDSOURCING FOR GOODS DISTRIBUTION

Many studies have been conducted about goods distribution in urban environments, recognizing both its vital character as well as numerous sustainability challenges it raises. These studies are important owing to the fact that most goods consumed in the cities are not produced in the cities, necessitating the transportation of enormous number of goods as well as garbage into and out of the city [76]. Urban freight transport

(UFT) enable activities towards wealth generation and industrial competitiveness, however, it also has detrimental social and environmental consequences, some of which includes road safety, fossil fuel consumption, air pollution, greenhouse gas emissions, noise, and traffic congestion. Furthermore, those involved in freight transportation have issues related to traffic flow, transportation regulation, loading/offloading, as well as customer service, all of which have an adverse economic impact [77]. Many novel solutions have been proposed to address these problems, with the majority of the proposal focusing on improving either passenger or freight movements. With the potential of massive data collection, crowdsourcing is considered as a useful technique for delivering potential solutions to challenges that are costly to solve traditionally.

Crowdsourcing is a tool for obtaining ideas and information from a large number of people in order to discover answers for a problem which would be difficult or impossible to resolve using different methods. There have been numerous recent studies that leveraged crowdsourcing for urban freight, but majority of these studies have been concerned with optimizing the last mile delivery logistics without adequately tackling congestion issues on these freights' routes [78], [79]. In this Big Data era, information and communication technology can be leveraged on to surmount constraints to smart freight, particularly as a result of infrastructure and equipment limitations for highway extension and investments [80]. As road congestion worsens, reliance on effective information and communication technologies via crowdsourcing could offer some solutions to smart freight mobility. There are unique challenges, especially in lowering fuel consumption, pollution, delay, safety as well as ton-mile traveled while maintaining freight performance. Effective strategies employing crowdsourcing could be created to enhance communication between trucks, evade traffic bottleneck spots along routes as well as reduce congestion in real-time.

The United States Federal Highway Administration (FHWA) and Federal Motor Carrier Safety Administration (FMCSA) conducted a joint modal 'smart roadside' program with a focus on smart freight mobility [81]. The scheme comprises technologies for improved roadside conditions and traffic information dissemination among trucks towards route planning as well as enhanced access to multi-mode ports, city pick-up and address for delivery, all of which are critical to the objective of the United States Department of Transportation (USDOT). One of the main aims of the scheme is to enable seamless gathering and dissemination of data among commercial vehicles, enforcement resources, roadway facilities, intermodal facilities as well as other transportation modes to increase the operational efficiency and mobility of freight [82]. Chandra et al. [82] developed a simulation framework that included a probabilistic modeling for making freight trucks smart – with enhanced mobility because of its ability to detour to evade a downstream congestion on the path. Data on impending congestion on routes are crowdsourced and leveraged by smart freight to detour. The authors designed a simulation model using discrete-time Markov chain (DTMC) to define the processing of detouring via closest exit ramp of a highway. The effectiveness of the model is substantiated based on the simulation analysis conducted with the average everyday traffic volume of both passenger cars and trucks utilizing interstate 405 (1-405) and 1-605 in the Southern region of California.

G. TAKE-HOME MESSAGE SUMMARY FOR CROWDSOURCING MODELS AND ARCHITECTURES IN TRANSPORTATION

The survey works in this section have uncovered the following points and take-home messages for crowdsourcing models and architectures in transportation:

- With the massive transportation data generated in a smart city environment, crowdsourcing models and architecture provides an effective process to collect and process these data to become meaningful for making informed decision. There are massive number of smartphones and embedded device that participate in data generation task which necessitate the need for a robust process to collate and process them.
- Connected and autonomous vehicles are equipped with sophisticated sensing, communication and processing abilities. Researcher can properly utilize these onboarding resources for sensing, communication and processing services for smart city transportation application without incurring extra cost of deployment. This will relieve pressure on existing infrastructure while also encouraging development of new smart city transportation application. However, how to effectively encourage vehicle owners to voluntarily share the onboarding resources for crowdsourcing task while addressing concerns such as energy usage in batteries and leaks in location privacy is still an open research.
- Vehicle Social Network (VSNs) presents another paradigm of crowdsourcing enabling passengers to utilize onboard devices to create and share contents of common interest within online communities while on transit. Such meaningful real-time information about traffic condition, road accident, and so on from passengers and onboard devices can enable other passengers make informed decisions.
- Crowdsourcing can enable seamless collection and dissemination of data among commercial vehicles, enforcement resources, road facilities, intermodal facilities as well as other transportation modes to enhance the operational efficiency and mobility of freight.

IV. ALGORITHMS AND TECHNIQUES FOR RIDESHARING AND CROWDSOURCING

This section discusses various algorithms and techniques which are utilized for ridesharing and crowdsourcing: (1) Matching algorithms and techniques; (2) Pathfinding, routing and scheduling techniques; (4) Heuristics and evolutionary computing techniques; and (5) Graph-based techniques. Table 3 shows a summary of algorithms and techniques for ridesharing and crowdsourcing discussed in the sub-section.

A. MATCHING ALGORITHMS AND TECHNIQUES

The matching techniques for ridesharing and crowdsourcing will significantly depend on the different scenarios to be considered. The authors in [83] give four scenarios for ridesharing systems: (1) Identical ridesharing – where the driver and passenger have the same origin and destination; (2) Inclusive ridesharing – where the passenger is on the way of the driver route; (3) Partial ridesharing – where the pick-up and drop-off locations of the passenger are on the driver route, but the origin or destination of the passenger is not on the way; (4) Detour ridesharing – where either the pick-up and/or drop-off locations are not on the way of the driver route. Several authors have proposed various approaches and techniques to meet the requirements for the different scenarios. In particular, dynamic ridesharing and scenarios poses many challenges to be addressed to match drivers and passengers on short notice in changing environments.

The authors in [84] give an earlier and illustrative approach for matching drivers and passengers in dynamic ridesharing scenarios. In this work, the authors developed optimization matching approaches with the goal to minimize the total system-wide vehicle miles and the individual travel costs. Their simulation results showed that the optimization approaches could significantly improve the performance of ride-sharing systems compared to rules based on greedy matching algorithms. The authors in [85] proposed a real-time approach for peer-to-peer matching for a flexible ride-sharing system. Their approach was termed ‘‘Ellipsoid Spatiotemporal Accessibility Method (ESTAM)’’ and generated a ‘‘time-expanded feasible network’’ for a searchable rider’s optimal itinerary. The ESTAM approach had three steps: (1) First, a geometric tool is used to identify the set of stations which are spatially reachable by each participant (driver or rider); (2) Second, the time intervals for each reachable station are found to form the set of feasible links for each participant; and (3) Third, the time-expanded feasible network for each rider is generated using the set of feasible links within the spatiotemporal vicinity of the rider. Their experimental results showed that their proposed matching algorithm could be applied in large-scale ridesharing systems and give results within seconds.

Some other approaches for matching algorithms for dynamic ridesharing can be found in [86], [87], [88], and [89]. The authors in [86] proposed a match making algorithm based on partitions. In their approach, the road network is divided into partitions for the search space. The authors define three categories of passengers: (1) Passengers who are about to start a trip and request a ride; (2) Passengers who have started their trip but have not been matched (i.e., these passengers are looking for other passengers to share their ride); and (3) Passengers who have been matched and are not available for further matches. Their optimization approach utilized two metrics, which are the mileage savings (S) and the sharing potential (R). Their experimental results used a case study by considering about 110,000 trips for the city of Singapore. Their work showed that for a single driver and a maximum detour of 10 minutes per passenger, the number of trips could be reduced by 42% and the daily mileage reduced by 230,000 km. There are two important considerations for the development of matching algorithms for dynamic ridesharing: (1) Objective function; and (2) Optimization parameters [90]. This is shown as a summary in Table 4 and Table 5 respectively. Other than road parameters, authors have also considered social preferences for the matching process such as age, gender, smoking, pet restrictions and the maximum number of passengers [91].

B. CLUSTERING ALGORITHMS AND TECHNIQUES

Clustering algorithms are powerful techniques used in machine learning for unsupervised datasets. Several authors have proposed to utilize clustering algorithms and techniques to address the issues faced in ridesharing and crowdsourcing systems. Some approaches to utilize clustering algorithms and techniques for ridesharing can be found in the works by [92], [93], [94], [95], and [96]. The authors in [92] proposed to utilize clustering techniques to identify high potential opportunities for ridesharing in pick-up and drop-off (PUDO) locations within transportation networks. The aim is to speed up the algorithm processing by identifying groups of similar nodes and put the nodes into a cluster. In their architecture, the nodes labeled A and B are the origin and destination respectively. For a ride to travel from A to B, it would need to pass through the five clusters shown as (blue, white, orange, brown and yellow). The authors denote this route as the ride cluster list. The effectiveness of the clustering approach will depend on how well the nodes that form the cluster are connected. Their approach utilized four algorithms: (1) k-means clustering; (2) Asynchronous fluid communities clustering; (3) Centroid-based PUDO placement; and (4) Congestion-based PUDO placement. The authors simulations and findings showed that the k-means algorithm performed poorly in comparison to the asynchronous fluid community algorithm. This was because the cluster connectedness could not be well inferred by its geospatial proximity. Their experimental results also showed that clustering methods could give effective PUDO placement to support the requirements for real-time and on demand ridesharing.

The authors in [93] investigated the dynamic ridesharing scenario where drivers and riders may have different origins and destinations. The authors proposed an approach termed as cluster-first-route-second to handle large-scale scenarios containing thousands of participants (drivers and riders). In this approach, the large-scale and computationally

TABLE 3. Summary of algorithms and techniques for ridesharing and crowdsourcing.

Focus area	Work contributions	References
Matching Algorithms and Techniques	Optimization approaches for matching drivers and passengers in dynamic ridesharing scenarios	[84]
	Real-time approach for peer-to-peer matching for flexible ride-sharing system (ESTAM)	[85]
	Matching algorithms for dynamic ridesharing	[86], [87], [88] and [89]
Clustering Algorithms and Techniques	Clustering techniques to identify high potential opportunities for ridesharing in pick-up and drop-off (PUDO) locations	[92]
	Cluster-first-route-second approach for large-scale ridesharing scenarios containing thousands of participants	[93]
	Clustering vehicle trajectories for ridesharing (TOPOSCAN)	[94]
	Formal connection between clustering and set partitioning for large-scale ridesharing	[95]
	Hierarchical clustering for ridesharing application	[96]
Pathfinding, Routing & Scheduling Algorithms	Ant colony optimization (ACO) heuristics and geosocial networks for solving ridesharing routing paths	[98]
	Theoretical basis and efficient implementation for empty-car routing problem in ridesharing	[100]
Task Scheduling, Assignment and Management	Heuristic greedy approach and algorithm termed as Saving Most First (SMF) to for task assignment	[103]
	Two-stage task assignment co-opetition model by utilizing three-way decision classification (TWD)	[104]
Machine and Deep Learning Techniques	Intelligent Complementary Ride-Sharing System termed as Plus Go	[105]
	Machine learning approach for package delivery framework through multi-hop ridesharing	[106]
	Distributed optimized deep learning framework for dispatching vehicles in largescale ridesharing (DeepPool)	[107]
	Deep reinforcement learning approach for joint passengers and goods transportation (FlexPool)	[108]
	Transfer learning for joint passengers and goods transportation (CoTrans)	[109]
Heuristics and Evolutionary Computing Algorithms	Heuristics and GA to address dynamic ridesharing where participants are formed at short notice	[111]
	PCSA (Parallel Scheme with Simulated Annealing) for dynamic ridesharing	[112]
	Hybrid SA (HSA) approach towards dynamic shared-taxi-dispatch	[113]

TABLE 4. Objective functions for dynamic ridesharing.

Objective function	Description
Total distance saved	Total number of mileages saved by passengers when driving compared to ridesharing
Total travel time	Total travel time for passengers from origin to destination locations
Total travel cost	Total travel cost for all passengers after sharing costs with other passengers
Total waiting time	Total waiting time incurred by passengers due to ridesharing
Total no. of passenger matches	Total number of passengers which can be (satisfactorily) matched

TABLE 5. Optimization parameters for dynamic ridesharing.

Optimization parameters	Description
Acceptable waiting time	Acceptable time for passengers to wait for drivers to pick them up
Acceptable walking distance	Acceptable walking distance for passengers who are willing to go to specified meeting points
Acceptable detour distance	Acceptable distance for drivers who are willing to change routes to pick up passengers
Acceptable no. of transfers	Number of times passengers are willing to change their transport vehicle

challenging problem is resolved by first decomposing into smaller problems by clustering. Their approach utilized two clustering techniques to identify high potential opportunities for ridesharing: (1) Greedy algorithm; and (2) k-means clustering. After the clustering process, each cluster will contain a driver and several riders. Their experimental results used benchmark datasets from [97] and showed that: (1) Both the clustering algorithms could give good solutions even for large (101 nodes) problems; (2) The Greedy algorithm outperformed k-means for most problems in the datasets; and (3) For a large cluster size (ten or more nodes), the objective performance was within 6.3% of the optimal solutions.

The authors in [94] proposed an algorithm termed as TOPOSCAN for clustering vehicle trajectories for ridesharing. Their algorithm can be applied towards multi-dimensional networks including traffic networks and social networks. The TOPOSCAN algorithm can be considered as a density-based clustering approach for paths where the density is given as the number of vehicles passing a link. Their experimental results utilized vehicle trajectory data for the city of Chicago. This is a large-scale dataset with 1578 nodes, 4805 links and 218 traffic analysis zones. Their work showed that their approach using shared vehicle trajectory data could reduce traffic congestion and give travel paths which are environment-friendly. The authors in [95] developed a formal connection between clustering and set partitioning and demonstrated the effectiveness of their approach towards solving the large-scale ridesharing problem. Their experimental results showed that by utilizing an Expectation Maximization (EM) clustering algorithm, their approach could reduce the total vehicle distance by 69% compared to a scenario without ridesharing. The authors in [96] proposed a hierarchical clustering approach for a ridesharing application. Their experimental results demonstrated high quality solutions and was able to solve problems involving thousands of agents in short periods of time (minutes).

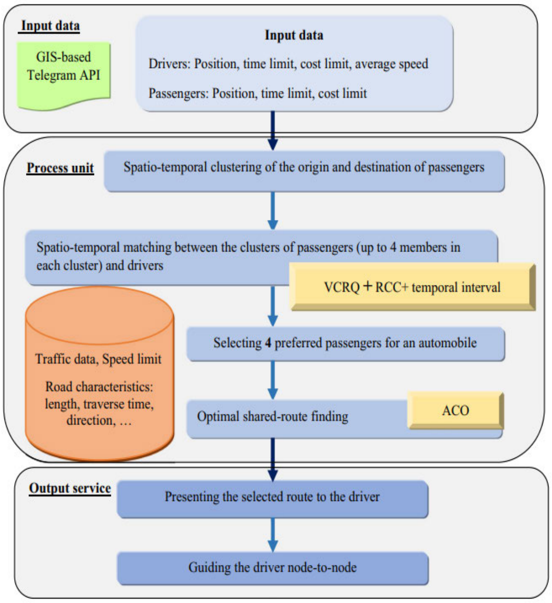


FIGURE 10. Overview of ACO hybrid ridesharing [98].

C. PATHFINDING, ROUTING & SCHEDULING ALGORITHMS

Another main design consideration for ridesharing is the utilization of pathfinding, routing and scheduling algorithms for optimization of the travel paths. An illustrative example can be found in the work by authors in [98]. In this work, the authors proposed to utilize the ant colony optimization (ACO) heuristics and geosocial networks for solving the routing paths for ridesharing. Fig. 10 shows an overview of their proposed approach which contains four stages: (1) Spatio-temporal clustering of origin and destination of riders; (2) Spatio-temporal matching between clusters of drivers and riders; (3) Maximizing number of riders for a vehicle; and (4) ACO for optimal shared routes finding. The first stage performs spatiotemporal clustering of riders using the k-means algorithm. The second stage performs spatiotemporal matching amongst the clusters of riders and drivers using the VCRQ algorithm which was proposed by Xuan et al. [99]. The third stage attempts to prioritize spatiotemporal relations with a maximum number of riders which in this case was four passengers. The fourth stage performs the optimal shared routes finding using the ACO. The ACO algorithm utilizes a nature-inspired heuristic which mimics the behavior of ants laying down a trail of pheromones to find optimal paths between two graph vertices. The authors tuned five parameters (number of ants, number of iterations, evaporation rate and two parameters to indicate the importance of the pheromone) in the ACO to optimize the path finding.

The ACO used an objective function which was defined to minimize the travel time, trip costs, total waiting time and total delay time. Their experimental results used a dataset for the city of Tehran with 70 drivers and 220 riders, and demonstrated that the ACO approach could give effective and efficient solutions when compared with other approaches for dynamic ridesharing.

The authors in [100] discussed the empty-car routing problem in ridesharing systems. This is an important problem because if a rider arrives in a region, and there are no empty vehicles, the rider would find an alternative form of transportation, and avoid the ridesharing mode. In commercial ridesharing systems, the empty-car routing model is realistic when drivers would roam to find riders. Their work gave a comprehensive solution for the empty-car routing problem which has a theoretical basis and is also efficient for implementation.

D. TASK SCHEDULING, ASSIGNMENT AND MANAGEMENT

Task scheduling, assignment and management are key components in crowdsourcing. In this subsection, we summarize the characteristics of tasks and review some specific works on the process of task management and assignment. There are two important issues: (1) Task characteristics; and (2) Task recommendation and assignment. Task characteristics is about extracting and categorize them to speed up the task assignment. Factors considered in the assignment and scheduling tasks are task feasibility, completion time, special factors, task complexity, task pricing and workers who consider the basic factors such as time, position, and preference in performing tasks. Task recommendation and assignment is about how the platform recommends tasks to interested participants after the evaluation of the participants. task assignments and recommendation methods can be summarized into assigning subtasks, participation information, and auction. Many task allocation algorithms have been proposed in the crowdsensing system aiming at various kinds of optimization goals.

The authors in [103] proposed a heuristic greedy approach and algorithm termed as Saving Most First (SMF) to effectively assign tasks. The SMF approach defines the distance between route and the task by taking the start and end points. To address the local optimal issue, the authors also proposed an optimized SMF based genetic algorithm (SMF-GA). The SMF-GA could address the effect of the sub-optimal issue to find the global optimum through the process of crossover and mutation. The authors evaluated the performance of SMF-GA algorithm using a large-scale real-world dataset called T-drive data. The dataset contains trajectories of 10,357 taxis within a city, and is used to model the location and movement of vehicles in the city. Their experimental results showed the proposed SMF-GA outperforms SMF, nearest first algorithm (NF), GA and nearest first-based GA algorithm (NF-GA) in assigning tasks and motivated more participants. Another approach by the authors in [104] proposed a two-stage co-opetition model by utilizing three-way decision (TWD) which is a new decision classification theory. Their work includes a competition-optimization model and a negotiation-cooperation model. The first stage is termed as the competition-optimization model where candidates compete with each other and an initial allocation can be obtained. The second stage is the negotiation-cooperation model. The aim of this stage is to protect the profits of the task candidates and optimize the total benefits. In the negotiation cooperation model, the k-fuzzy measure is used to calculate the generalized cooperation relationship of candidates.

Luo [101] proposed a mathematical modelling approach for managing assignment of requests in a centralized platform using multi-criterion many to many assignment optimizations. The approach also employed prospect theory for making optimal bid to decentralized individual driver for multiple assigned requests. They validated their framework using the taxi yellow cab data collected from New York City in 2017 in both demand and supply perspective. Their work attempted to predicted Uber-like ridesharing trip demands and driver supplies so that such information be used in subsequent multi-criterion drive-to-passenger assignment and driver's prospect maximization models. It can further predict the ridesharing demands and supply within certain census track at a given hour.

Zheng et al. [102] proposed a task scheduling scheme to minimize the total distribution path length when all tasks are assigned. They designed a variable neighborhood search algorithm (VNS) with four neighborhood operation and set a selection probability for every operation to minimize the algorithm's solution time. They further implemented a heuristic solving algorithm for a comparison experiment. The results of the experiment showed that VNS algorithm has a higher solving quality.

E. MACHINE AND DEEP LEARNING TECHNIQUES

This subsection discusses different types of architectures, techniques and application of artificial intelligence (AI) and machine learning towards the problem of ridesharing and crowdsourcing. An illustrative approach towards applying these emerging technologies can be found in the works by Wickramasinghe et al. [105]. In this work, the authors proposed and implemented an Intelligent Complementary Ride-Sharing System termed as Plus Go or +Go. The major blocks are: (1) User profile management; (2) Registration/validation; (3) Rating maintenance; (4) Optimum path recognition; and (5) Dynamic fare calculation. The first-time user needs to register and verify their mobile number, followed by validation and profile creation. The ride-matching algorithm will recommend the list of drivers to the passenger based on the destination. There are two stages in this algorithm. The first stage is to choose the driver list that matches the requirements e.g., destination, time, etc. The rule-based machine learning is used to select the suitable drivers for a passenger. The second stage groups those drivers into specific clusters and identify the most suitable driver. The drivers from previous list are clustered based on their profession and others, followed by right cluster extraction. +Go also enables the rating of the passenger from drivers. The naive Bayes machine learning classifier is used to classify the probability of words in sentiments and give the rating. +Go also estimates the traveling cost according to the travel distance, time to destination and the vehicle fuel consumption. A multiple linear regression model is applied to predict the fuel consumption. To identify the shortest route, Dijkstra's and the Travelling Salesman Problem algorithms are used. Their experimental results showed that the +Go system could achieve an accuracy of over 85%.

The authors in [106] proposed a machine learning approach termed as PPtaxi which is a new package delivery framework through multi-hop ridesharing. In this scenario, a package is assigned to a taxi for delivery when transporting the passengers. The PPtaxi framework has two phases: (1) Passenger order prediction – determine the probability of passenger flows across the city at different time slots, based on the historical data of passenger orders and the calculation of the departure probability, destination probability and flow probability; and (2) Package route planning – determine the optimal route planning algorithm (DOP) using the predicted passenger orders. The Passenger order phase utilizes the Multivariate Gauss distribution and Bayesian inference to perform the prediction. The Package route planning phase utilizes the Dijkstra based optimal route planning algorithm (DOP) using data on the predicted passenger orders. The experimental results were performed and evaluated on a real-world dataset obtained from an online taxi-taking platform and showed that PPtaxi could give an average 95% delivery rate of packages.

Recently, several authors have proposed utilizing deep neural network and transfer learning techniques and approaches towards the ridesharing problem. Examples of deep learning approaches can be found in the works by Al-Abbasi et al. [107] and Manchella et al. [108]. The authors in [107] proposed a distributed optimized deep learning framework for dispatching vehicles to customers in largescale ridesharing and carpooling systems termed as DeepPool. The DeepPool architecture has the capability to perform multiparameter optimization objectives such as minimizing supply and demand mismatches, rider waiting time, number of vehicles, fuel consumption and traffic congestion. The DeepPool architecture contains various components for computation and communications. The Control Unit maintains the various states such as current location, destination, and vehicle occupancy. The deep queue networks (DQNs) dynamically compute the optimal values for the dispatch actions in different states. The distributed DQN policy learns the optimal dispatch actions for each vehicle which can decide its own action using a Q-learning method without coordinating with all other vehicles and consequently reduce the complexity. Their experimental work used a real-world dataset of taxi trip records from the city of New York, and demonstrated that the DeepPool architecture could significantly reduce the number of operating vehicles, wait time of passengers, and traffic congestion.

Recently, authors in [108] proposed a new deep learning approach for joint passengers and goods transportation termed as FlexPool. FlexPool utilizes deep reinforcement learning algorithms and was designed as a multihop transit technique to pool passengers for ridesharing and goods for delivery. The Flexpool framework aims to optimize several objectives: (1) Minimize the demand supply mismatch; (2) Minimize the time taken to pick-up an order; and (3) Minimize the additional travel time incurred by orders. These objectives are incorporated into the objective function for the deep learning. For distributed dispatch, reinforcement learning is used to learn the probabilistic dependence between vehicle actions and the reward function. Their algorithm uses a term known as hop-zones which are pre-determined locations on the map. Heuristics are used to assign hop-zones for the goods delivery requests. The algorithm then determines the best matches for the pick-up request from the passengers and goods for each vehicle. Their experimental work used a real-world dataset of taxi trip records from the city of New York, and demonstrated that the FlexPool architecture could significantly increase the fleet utilization and fuel efficiency.

The work in [109] demonstrates an approach to utilize transfer learning for joint passengers and goods transportation in ridesharing systems. The work in [109] demonstrates an approach termed as CoTrans to utilize transfer learning for joint passengers and goods ridesharing and transportation. The work addressed the issue of unauthorized ridesharing by detecting the trajectories of ridesharing cars from a pool of cars. Their algorithm uses a two-stage transfer learning approach: (1) Source-Target Domain Linking – in this stage, vehicles (taxi and bus) data in the source domain are input to a random forest classifier which detects and labels the candidate cars in the target domain and classify them to form the initial training set for the next stage; and (2) Target Domain Co-Training – in this stage, co-training with a second classifier (a convolutional neural network (CNN)) is utilized to enrich the ridesharing features to increase the classification rate. The CNN architecture contained several convolutional layers and max-pooling, a fully connected layer and an output layer with a sigmoid function. The CNN is used to extract the car driving patterns from the trajectory image and predict the ridesharing probability. The ensemble of the random forest and CNN was used to determine the final label of each candidate car. Experimental results on real-world car, taxi and bus traces showed that the CoTrans approach could outperform other transfer learning methods, while not requiring the dataset to be prelabeled and gave a performance accuracy comparable to human labeling.

F. HEURISTICS AND EVOLUTIONARY COMPUTING ALGORITHMS

There are two main categories of techniques for the ridesharing problem: (1) Exact methods; and (2) Heuristic methods.

Some examples of exact methods are branch-cut-and-bound, integer programming and column generation. Some examples of heuristic methods are local search techniques and greedy algorithms. The authors in [110] proposed an optimization approach for dynamic ridesharing using a randomized greedy search to minimize the total driver travel costs and maximize the number of rider requests. Some authors have also proposed using evolutionary computational techniques and heuristics such as genetic algorithms (GA) and simulated annealing (SA) towards the ridesharing problem. The authors in [111] proposed utilizing heuristics and GA to address the dynamic ridesharing where the participants are formed at short notice. The authors term this as the ride matching problem with time windows (RMPTW). There are two stages in their approach: (1) The first stage used a GA; and (2) The second stage modifies the GA to perform the ride matching in real-time. Their approach considers the ridesharing problem as an optimization problem with a multicriteria objective function to minimize the total travel distance and time of the drivers, total travel time of the riders and maximize the number of riders. Their GA approach used crossover and mutation operators. The authors used a single-point crossover by exchanging routes among parents and defined five mutation operators (push backward, push forward, remove-insert, transfer mutation and swap mutation) for the GA. For example, the swap mutation operator selects a randomly selected point in the route and swaps with a neighboring point. Their experimental results on real-world datasets showed that their approach could give solutions for real-time dynamic ridesharing and could be tuned to balance between the solution quality and the time responsiveness.

The authors in [112] and [113] proposed using SA to address the optimization requirements for dynamic and real-time ridesharing. SA algorithms are global optimization approaches which mimic the process of physical annealing. The algorithm has three components: (1) The cooling schedule to determine how the temperature reduces from a high initial temperature; (2) The move generation to generate a new state from the current state; and (3) The stopping criteria which will terminate the SA process. The authors in [112] proposed an algorithm termed as PCSA (Parallel Scheme with Simulated Annealing). Their algorithm utilized an exponential cooling schedule. For the move generation, a candidate vehicle is randomly picked and there are two scenarios: (1) Insertion scenario – if the vehicle is at maximum capacity, a request in the vehicle schedule is removed randomly; (2) Move scenario – if the vehicle is at maximum capacity, a request is picked randomly to make an exchange. Their experimental results used a dataset for the city of Manhattan and demonstrated that PCSA could efficiently solve the global optimization problem for ridesharing and outperformed other approaches. This is a large-scale ridesharing scenario with 4411 nodes and 9618 edges. The authors in [113] proposed a hybrid SA (HSA) approach towards the dynamic shared-taxi-dispatch problem. The algorithm objective is to take a service request from a queue and locate the best available taxi within a time window and determine the optimal route to meet vehicle capacity and time constraints of passengers. Their experimental results used a dataset for the city of Seoul with 6321 nodes and 8382 links and demonstrated that the HSA approach could give effective solutions and maximize the efficiency of dynamic ridesharing.

G. TAKE-HOME MESSAGE SUMMARY FOR RIDESHARING AND CROWDSOURCING ALGORITHMS AND TECHNIQUES

The survey works in this section have uncovered the following points and take-home messages for ridesharing and crowdsourcing algorithms and techniques:

- The ubiquity of mobile internet technology has opened up new ways to connect people who have similar travel plans and availability for last minute ridesharing. Smartphones with internet access enable dynamic, on-demand ridesharing by enabling users to offer and request trips whenever they want from any location. Great research efforts have been geared towards developing algorithms and services for optimally matching drivers and riders in real-time and enabling dynamic ridesharing as part of sustainable urban mobility.
- Clustering algorithms and techniques have been employed in quickly evaluating the possibility of ridesharing in urban environments facing the challenges of large number and diversity of origin and destination locations. Implementing pick-up and drop-off (PUDO) locations within the network can simplify ridesharing heuristics, allowing more accuracy in online ridesharing. More research is needed to implement more powerful clustering algorithms and techniques to quickly identify efficient ridesharing opportunity.
- The use of machine learning and deep learning algorithms and architectures for dispatching vehicles to riders in large scale ridesharing and carpooling systems are coming to the forefront. They offer the advantage of achieving multiparameter optimization goals such as reducing supply and demand mismatch, rider wait time, number of vehicles, fuel usage and traffic congestion. They further provide the advantage of computing and learning of optimal dispatch actions for each vehicle which enables it to decide on its own actions without consulting with all other vehicles which consequently reduce the system complexity.
- Many studies have considered the dynamic ridesharing problem as an optimization problem and employed heuristics and evolutionary computing algorithms and techniques to address it. The results of some the studies [110], [111] show that these techniques can optimize dynamic ride-matching, minimizing the riders' total travel time and maximizing the number of riders transported.

V. SOCIAL ASPECTS: SECURITY, POLICY AND PRICING

This section focuses on the aspects of security, policy, and pricing in ridesharing. These aspects involve both the driver and the passenger involve in the ridesharing. Security and pricing are a major concern for passengers because every passenger want security and effective low cost for their ridesharing.

A. SECURITY & PRIVACY

This subsection presents security and privacy which are a major concern for passengers because of the risk of sharing their information. Many passengers are reluctant to involve in ridesharing because of privacy and security issues. These risks include exchange of confidential information relating to location, travel destination and time spent riding with strangers. Those involved in ridesharing network also face risk to financial details which are required to pay for services and location data shared on network. This confidential information derived from passengers are usually shared with the service, generating concerns for the possible abuse of privacy.

The authors in [114] developed a model that only permits dispensing of sensitive information to devices on network with trusted status. The method captures information for journey in terms of traveler's trajectory and final destination. This limits potential users to access information on ride segment based on their intended direction of travel without divulging information on joint commuters' location thereby protecting privacy without a sacrifice of ridesharing functionality. The tool proposed was named PrivatePool which hinges on two major properties to drive privacy-preserving ridesharing. The first is identification of distance between start and endpoints of the proposed journey and the next being intersection of the routes along that trajectory. A protocol was developed with the aim of utilizing proximity between journey points to determine ridesharing potential for any given trip. The methodology inherits some of its characteristics from homomorphic encryption and its application in establishing privacy within a network. The trajectory matching technology involves a novel threshold private set intersection (T-PSI) protocol, designed to provide technical improvements to threshold key encapsulation mechanism (T-KEM) creating additional stated benefits of rigorous privacy guarantees. The outcome is a situation where ridesharing information is only provided if there is a high probabilistic match for the parties involved.

The authors in [115] proposed SmaRi a ridesharing system capable of interfacing drivers and passengers. The SmaRi design incorporates three service layers: the registration layer, transaction layer, and cash layer. These all function as a system providing solutions for different service processes such as confirmation of identification, positive ride matching, payment transactions, and accounting services. The system functions utilizing social networking service (SNS) such as a user's friends list and support information such as user IDs and Ethereum addresses to facilitate ridesharing arrangements. Utilizing the blockchain as its base technology, incorporates a decentralized system that provides architectural benefits and supports optimized computing by distribution of the governance function. Personalized data such as driver's licenses and vehicle information are captured as a requirement for setting up summary contracts (SC), which are a set of specialized smart contracts that establishes relationships between users within ridesharing arrangements using key information captured in user data. The utilization of blockchain technology in SmaRi increases the flexibility of ridesharing arrangements. In SmaRi, blockchain nodes are involved with data exchange based on machine-to-machine trust. This is made possible by a consensus-based algorithm which substitute the need for trust among users. Utilizing the blockchain technology as a means of distributing data storage requirement provides information security without involving third-party application. A unique feature of the blockchain technology is its ability to create duplication of data across several nodes enforcing a consensus for any data to be verified. The SmaRi system utilizes this feature to ensure attacks on any single node does not have a compromising effect on the entire system. The technology behind SmaRi distinguishes it from other existing ridesharing systems such as Prearranged Plan and Automatic Execution, Security and Data Storage, Decentralized Organization and Cost Reduction.

The authors in [116] proposed a ridesharing system named GreenRide. The system utilizes Google Firebase for ease of integration, security, and data regulation. The data gotten from all employees are kept only in the organization database while the data of those involved in ridesharing are kept in the Google Firebase. This provides a feeling of safety for user of the service. The design of GreenRide system involved two components. The first component being the centralized application code which is hosted on the engine of the Google Cloud App. This creates an automated information generation system during the peak hours of ridesharing. The next component is the decentralized rewarding of Green Ride Tokens (GRTs) which utilize the Ethereum blockchain on a Private Network still within the Google Cloud App Engine. GreenRide rewards users of the platform with GRTs keeping them aware of volume of CO_2 emission averted per ride they share.

B. POLICY & ENVIRONMENT

This subsection presents policy and environment in ridesharing. Ridesharing has a positive impact on environment as it helps to decrease the traffic jams, air pollution, emission of carbon and other CO_2equivalents. Commitment to environmental policies is needed to ensure reduction in carbon footprint. The technical inputs and ridesharing requirements of GreenRide [116] encourages users to promote environmental best practices. The magnitude services of the ridesharing service controls deployment of vehicles to match demand thereby reducing the overall contribution to traffic, carbon emission and other forms of pollution. A novel achievement within the research is the integration of reward systems utilizing blockchain technology that is capable of generating interest in ridesharing amongst users and non-users alike.

The authors in [117] inferred regulatory authorities have unexplored opportunities to deploy policy tools that incentivize ridesharing and could boost overall participation and gains derivable from sharing. Some of the recognized benefits include reduced costs, pollution, and lower traffic density for both individuals and the entire community. The algorithm developed promotes the feasibility of large-scale peer to peer ridesharing with a clear depiction of the likely environmental gains inherently possible. The author utilized data from the New York city cab pool capturing variables relating to vehicle occupancy, changes in travel distance and number of trips taken to evaluate environmental gains. Gains considered include CO_2 emissions and noise pollution reduction. These deductions become applicable tools in the argument for policy establishment to further environmental objectives. The authors in [118] proposed a means to improve business trip ridesharing possibilities by application of the Green Information Systems (Green IS). A tool conceptualized with environmental sustainability as its primary focus. To achieve this, the author combines the theory of Planned Behavior with the Technology Acceptance Model for a Western European company with a sample size of 211 employees to establish observable comparison between employees' Green Information Systems (IS) usage and real-world behavior.

The authors in [119] proposed a multi-class ridesharing assignment framework that applies logit-based technology to achieve equilibrium assignment of ridesharing resource. The research examines several ridesharing equilibrium models and examines the policies considered in their design. The application of multi-class is designed to account for differing passengers and their mode choice behavior. The framework was formulated as a mixed complementarity problem (MCP) and attempts to develop a hybrid policy that covers situations requiring car restrictions, cordon tolling and subsidization. Transportation fares are assumed to be distance based and proportional to in-vehicle transport cost. This information is used to develop a multi-class ridesharing stochastic user equilibrium problem, an MCP applying numerical methods. As part of outcomes, observation was made beyond choice of users travel preference, policy was more influenced by how well different transport modes performed. A comparison between the car restriction policy and the cordon toll policy was made. The policy of car restriction is found to no longer take effective when total demand is lower than the maximum cars captured in CBD. The two policies when compared show the Cordon policy toll is more effective in Urban control. For verification of observed results, a car restriction was placed on the access links to the CBD (links S3 and S4), and in a second experiment, cordon tolls were applied at same CBD links.

The results were also compared with the do-nothing case (i.e., case 0). From the result, it is first noticeable that case 2 outcomes exceeded case 1 proving that "cordon toll" policy offers better results than "car restriction" policy when cumulative growth of social surplus is measured. As a second point of note, it indicated that very well-developed transit system such as that in Hong Kong which make use of entry toll to the CBD as a stimulant for shared rides will find that they will experience the limitations highlighted in this research on effort to improve system performance. Also, the effects of subsidized cost of ridesharing utilizing the proceeds of social surpluses gained from cordon tolls will yield most effect for ridesharing when alternative transport modes perform poorly.

C. PRICING & PARKING

As discussed in preceding sections, ridesharing has a potential to reduce traffic congestions and parking requirements. This subsection presents pricing and parking which are fundamental aspect of ridesharing; Pricing determines values ridesharing participants exchange as part of the system. For ridesharing to be feasible, it becomes important that prices in the system are more attractive than other options or at the least competitive. The methodology of fuel cost split, parking, and how ridesharing providers obtain their payments as part of the business model.

The authors in [83] classified pricing into three types namely, catalog price, rule-based price, and negotiation-based pricing. The authors in [120] proposed a "No Preemption auction"; a system that has properties that promote budget balance, truthfulness based on risk aversion hypothesis, data accuracy, and clear decision rationalization. The system establishes a competitive bidding situation for available rideshares using an online auction channel. In ridesharing, auctioning will take the form of dynamic costs, creating a model which differs significantly from most existing auction systems thereby offering a unique set of challenges. The auction models considered as part of this scheme include one-side auctions and sealed-bid auction models. In both cases, the passengers are bidders, the platform constitutes the auctioneer offering up available seats in the shared ride as the object of interest. Cost of rides is then determined by the final pricing that allocates a seat to any given rider. Their experiments involved the real taxi-trace dataset of Shanghai obtained in 2015. As part of the research, the worst performing scenarios were captured which depicts situations where auction costs fail to justify total travel time measured in competitive ratios. There is also a benchmarking of social welfare performance which involved comparing online auction deployments with regular rideshare models. This resulted in the conclusion that with regards to social welfare maximization in ridesharing, online platforms were less beneficial especially using models involving auctions.

The authors in [121] proposed a method to manage situations of ride shortages where seats are made available to those who want it the most, represented by passengers who are least price sensitive. The platform consists of an auction-based pricing mechanism where users submit their best bids that represent what they are truly willing to pay in bonus bids.

The platform then responds by creating order dispatch and reflecting accepted pricing. The author identified two methods that could achieve this outcome one of which is the use of greedy algorithms that could deploy a problem-solving heuristic. The second was a ranking approach that prioritizes order dispatch by pricing advantage. Through analysis of literature and experimental data, it was concluded that ranking-based algorithms fit the structural requirements. The choice is credited on analysis of benefits to the ride-giver as mark-ups are more attractive in cases where the intendent commuter (which is a buyer in this scenario) is given the opportunity to set pricing devoid of capped rates. Auction detailing require buyer to state point of origin and desired destination along with a price offer. The provided information is computed and marketed to the drivers on the platform. The platform computes accepted offers and allocates rides. Final payments are then generated according to bid prices within the platform.

In the work by Dong & Leng [122], ridesharing was conceptualized with a view to direct charges for rides directly to the ridesharing services platform and not directly to drivers on the platform. The idea involves creation of wage structures based on completion of ridesharing service. Analysis of the concept was structured as a choice problem for a passenger between a shared ride and taxi service including the option for drivers who can opt in and out of rides. Sensitivity analysis was used to generate the platforms optimal service pricing per passenger and corresponding wage payments for drivers. The profitability of the model is found to be higher when there is a combined saturation of rides and passengers with a larger percentage opting for taxi services. The research identifies the ability for passengers' perception of rides cost to drive prices upwards and increase margins for the platform operators. However, base fares, base wages, and charges per kilometer dominate the ride pricing system. The author also indicates the application of dynamic pricing to improve marginal profits as certain parameters such as ride demand, driver availability, cost perceptions, operational costs amongst other variables change.

The authors in [123] identified the impact of parking competition in ridesharing and proposed a parking fees discount that encourages ridesharing in commuter. In an attempt to solve the problem, the authors proposed an equilibrium model that considers optimal parking density and the behavior of the user in ridesharing. The objective of the model was to utilize mode of commute, length of trip and competition for parking spaces to develop an effective ridesharing as a solution for traffic congestion. Two approaches were developed as possible solutions to the problem. The First solution involved a decision-making process to balance commuter cost and infrastructural cost. The second solution focuses on an incentive scheme targeted at shared rides. Discounts were given to vehicles involved in ridesharing for parking advantage. Establishing the ride balance between charges for parking and convenience for riders leads to trade off considerations. As parking spaces increase, so does construction cost. The alternative represents significant cost to vehicle users. The research indicates that up to 50 percent savings can be obtained by users involved in ridesharing, which theoretically attracts all commuters in the direction of sharing arrangements.

The authors in [124] investigated ridesharing policy under three distinct schemes. The schemes include a variable parking fee with constant fee ridesharing condition, a scheme where both conditions are held constant and a third option for constant parking fees with variable ridesharing costs. These are benchmarked against a case of no ridesharing. The aim being obtaining a combination that eliminates bottleneck situations heralded by traffic density. For this purpose, homogeneity of travelers is assumed attributing same value-of-time across all commuters. Analysis of the various method in ridesharing pattern and parking fees was done with the following parameters distance travelled, time spent and cost of the journey to evaluate the overall performance of the system. Based on outcome of the research, the regular parking fees and ridesharing does not show any remarkable change in the efficiency of the system during morning rush hours with single driver arrangements. From assessments of available policy options within differing configurations, conditions involving dynamic parking fees with structured systems for ridesharing can provide a better overall user experience in terms of delays experienced resulting from traffic related issues.

D. ATTRIBUTES & BEHAVIOUR

This subsection presents the attributes and behavior of passenger in ridesharing. Passengers are found to be most driven by satisfaction levels in ridesharing, a situation which in itself requires favorability in variables such as time spent travelling, journey cost and acceptable rider matching in shared rides.

The authors in [125] proposed the concept of Dynamic Ridesharing Optimization using Social Preferences (DROPS), a dynamic ridesharing framework that considers social factors such as age, gender and previous ratings for rideshares as a means of decision making for pairing commuters in any rideshare. The possibility of greater compatibility in matched riders presents an opportunity for increased participation by long term and first-time users. An inclusive variable that was identified as a possible consideration for improvement was how quickly a rider needed a ride. The identified factors responsible for determination of users' willingness to share rides are a result of feedback obtained from users. The users' preferences are depicted as +1, -1, or 0 which represent willingness, indifference and unwillingness to participate respectively based on certain interest points for users. Thus, the passenger value hinged on the ability of passengers to report compatibility on conclusion of rides in shared arrangements. Two variations of solutions exist to facilitate ridesharing setup. The methods indicated are trip formation and trip dispatch.

In the trip formation option, riders and vehicles are matched using a greedy algorithm to identify best suited rider-vehicle pairs. If the criteria for a trip to offer value beyond a certain benchmarked price, the said trip is set aside and a new one is setup. In the trip dispatch option, there is a need to fulfil either one of the following conditionalities; either the value of a given trip exceeds the pricing benchmark or a queued request has been left unattended for long periods without fulfillment. One this time limit is set it the algorithm functions to allocate greater priority to trips that have been queued for long periods over newer ones with higher pricing. The use of social factors for ridesharing options shows a marked overall potential to be more satisfying since it takes a more customer centric approach to address the challenges associated with the development.

The authors in [126] conducted a scenario-based study constituted of three hundred respondents to identify from consumer perception, why people rideshare. The questions posed to the research subjects included 17 questions relating to personal attributes, 7 questions to develop clear context and 7 relating to demographics. In this research, several hypotheses from authors developed over the years around antecedents towards ridesharing participation are examined. From the research subject feedback captured, a relationship was drawn between anxiety during road commute and interactions such as road constructions, gridlocks and pedestrian interfaces. Potential users exhibit a greater tendency to involve in ridesharing if trust can be established as a basis for travel relationships between co-commuters and service providers alike. These requirements are coupled with the need to obtain further benefits in terms of cost savings and favorable travel times.

Applying structural equation modeling (SEM), the different drivers of attitude towards ridesharing and intention to rideshare were identified and analyzed using the method of Partial Least Squares-Structural Equation Modeling (PLS-SEM). In the construction of the research hypothesis, a hypothesis H1 was constituted representing the influence of attitude towards ridesharing. Another hypothesis H2 was developed to measure the willingness of vehicle owners to participate in rideshare arrangements to aid others for commute. H3 was a measure of the belief some had in future rewards resulting from providing help to others. H3, H4 and H10 were synthesized to establish intention while all other hypotheses were geared towards measuring the impact of attitude. From the analysis, seven out of the 11 hypotheses proposed were confirmed from the structural model. The R^2-values measured for attitude towards ridesharing and participation intent are 0.505 and 0.729 respectively representing a model with high credibility.

E. TAKE-HOME MESSAGE SUMMARY FOR SOCIAL ASPECTS

The survey works in this section have uncovered the following points and take-home messages for social aspects:

- Security and privacy abuse are a major concern deterring users from getting involved with ridesharing, fearing that data about their location, travel destination, time spent on rides and financial details could be compromised. The use of blockchain technology for security and privacy preserving ridesharing system has been proposed [115] which promises to offer passengers automated execution and immutable record, as well as more decision-making power distributed from centralized organization to passengers. More research is needed on integrating blockchain techniques into ridesharing systems.
- Ridesharing is expected to have major environmental and economic impact by minimizing CO_2emissions, noise pollution, energy consumption, traffic congestion. However, despite these incredibly positive prospective benefits, very few passengers have adopted ridesharing solution. This is as a result of regulatory authorities' inability to evaluate the costs and benefits of a certain of a certain ridesharing policy due to the lack of effective incentive policies. More increasing research efforts and technology are needed towards ridesharing system along with novel incentive policies and effective market design. This will be essential for utilizing ridesharing to the fullest extent possible and for transforming the current mode of personal transportation.
- Prices in the rideshare system must be more appealing than alternative options, or at the very least competition to promote passenger participation in ridesharing. Ridesharing platform are expected to implement pricing strategies and auction mechanism following preferred pricing rules while considering factors such as rush hours, seat resources waste and so on.
- Aside from cost and time of travel, social compatibility with co-passengers is another critical factor that determine passengers' satisfaction in dynamic ridesharing. There is need for ridesharing services to implement frameworks that take the riders' social preferences into account during the matching process. This will enhance the quality of trip created, and optimize the operational value of rideshare providers while also maximizing trip value for passengers.

VI. USE CASES AND STUDIES FOR SMART CITIES

Several practical deployments have been reported for ridesharing and crowdsourcing in smart cities. This section discusses various use cases and studies for ridesharing and crowdsourcing which have been deployed and/or proposed in smart cities.

A. USE CASES FOR RIDESHARING AND CROWDSOURCING IN PARIS

The authors in [127] conducted a sensitivity analysis to highlight the potential of ridesharing regarding the reduction of congestion and mitigation of pollutant emissions in Paris, France. In their work, a multimodal static macroscopic transport model (MODUS) was applied to model travel demand

and conduct transportation studies within the city. The integration of MODUS with a land-use model (NEDUM) created an opportunity for measurements of accessibility within the city which influences the location of households and possibility of changes in land-use while capturing the potential for ridesharing. Data from the simulations were used to develop quantitative analysis utilizing measurements of congestion, changing travel behaviors and reduction of emission due to vehicle pollution in Paris.

MODUS was able to generate 1289 traffic analysis zones while NEDUM zoning was based on 1300 municipalities within Paris 12,011 km^2 area. Performance evaluation criteria were deployed to comprehensively investigate the influence of ridesharing. Inclusive are number of unit private vehicles (UPV), network congestion ratio, and volume of CO2 emissions while factoring in variables relating to Morning Rush Hour (MRH) and Evening Rush Hour (ERH) these offering indicators of major traffic congestion. The author explores two possibilities for analysis. The first is the no-differential growth of ridesharing (NDGR) where results of the analysis displayed constitutes of four data points representing uniform progression in occupancy rates ranging from 25% -100%. The alternate methodology referred to as the differential growth of ridesharing (DGR) where there is a dependency on trip distance to determine vehicle occupancy. Further considerations include the cost of operating private vehicles in ridesharing arrangements based on the assumption that costs were shared by vehicle occupants especially in DGR models. The results of simulation showed approximately 40% reduction in overall emission with full implementation of ridesharing in Paris region. The observed reduction of Unit Private Vehicles in Morning Rush Hour scenario exceeded the Evening Rush Hour. A phenomenon that was attributed to possibilities such as after work preferences or staggered peak periods for the sample population. Ridesharing yielded greater percentage efficiency in NDGR with 4% and 17% in MRH and ERH respectively as opposed to the 2% and 12% congestion reduction displayed in DGR.

B. USE CASES FOR RIDESHARING AND CROWDSOURCING IN BERLIN

The authors in [128] utilized data from Berlin's taxi fleet to evaluate the potential for shared rides with a capacity constraint of two and four requested rides. The constraint of two represents instances where taxi dispatches are capable of fulfilling rides while the requirement for the constraint of four depicts situations requiring a mini bus for ride fulfilment. Using an insertion-based algorithm, the conditions were dynamically captured within a full-stack transport simulation. The simulation software of choice was MATSim which deploys a fast queue-based model to imitate the flow of traffic. The simulation captures representation for shared autonomous vehicles, demand responsive transportation and taxis. For the purpose of routing taxis, an insertion heuristic is used that carries the property of being able to minimize time stretches in request handling for shared rides to meet up constraint requirements. The research highlights some limitations to the simulation efficiency as violations in designed wait time and travel time constraints may occur resulting from realistic delays experienced by rides in traffic situations.

The modelled dataset is managed for optimized performance using a set of key performance indicators. The indicators include average customer wait times, time spent onboard vehicle, boarding time, and an empty-to-total milage ratio for the entire fleet. The established model applies consideration of real-time constraints in providing dispatch for riders in shared rides. The representations: $\alpha \geq 1$ and $\beta \geq 0$, show time lost to waiting for rides, boarding, and rerouting during trips. The design incorporates the possibility for ride rejection in situations where some criteria is not met, or constraint is violated. As a ride is scheduled, the possibility for cancellation is nulled. Even in cases where rides fail to meet a certain constraint after scheduling, cancellation is still not possible as scheduled rides must be completed.

The dataset applied in the simulation was a representation of a typical Tuesday in 2013 where Taxi Berlin's fleet experienced about 63% utility. The city of Berlin experiences an excess supply of vehicles per passenger leaving each ride with an average 30% utility rate. Demand surges are experienced during morning rush hour and evening extended peak hours where there is a large volume of returning workers. A total of 180 runs of the simulations were executed with 60 runs per scenario (2,3,4). Many runs ended up as singularities and 24 conforming to expected outcomes. The results showed that in wait times and ride cancellations, the base case was outperformed. For vehicle capacities of 2 and 4, average wait time was lowest. However, in consideration of capacity, the minivan category performed marginally better.

C. USE CASES FOR RIDESHARING AND CROWDSOURCING IN ADELAIDE

The authors in [129] takes a look at the ridesharing technology divergent from the typical analysis of its efficiencies and its utility. Their research focuses on dissecting the characteristics, behavior models and motivations of non-users of the technology as this would be a major factor in trying to influence the shift in urban areas from private vehicles to ridesharing usage. The study examines Adelaide city the capital of south Australia with a population of 1.3 million residents which was considered a suitable context as its populace represents some of the most car dependent regions. The review of relevant literature led to the highlight of three major deciding factors; transport priorities, socio-economic characteristics and built environmental characteristics. The subjective transport priorities relate to the desire of commuters for comfort and convenience. The research also highlights the hesitance of female riders to share vehicles with strangers that are likely male. Further considerations are time flexibility, parking availability and its adaptations for a healthier lifestyle.

Socio-economic characteristics cover issues related to age category, education levels, race, and income levels. These conditions are observed to be responsible for many ethnic people of underrepresented groups using the service more than their local counterparts, a situation relatable to their income level. The impact of manmade environment variables on ridesharing is still unclear. Variables considered relate to human population density, land use patterns, street network design, city road networks. The researcher used data from the survey to analyze the impact of socio-economic issues and transport priorities to ridesharing. The analysis involved quantitative data obtained from Adelaide between the month of February and March 2018 with the help of CRC research node for Low Carbon Living in Australia. In the survey carried out, six points of interest were captured in the city of Adelaide. Individual who had visited this location from area within the city constituted the target sample. The area of interest includes Adelaide Oval; Royal Adelaide Hospital; Adelaide Station; University of Adelaide; Rundle Mall, and Adelaide Central Market.

During the survey, 422 respondents were identified. From the six locations, an average of seventy questionnaires each were obtained. Those from distances exceeding 60km were considered outliers and left out of the sample. Questions were centered around the earlier identified deciding factors namely transport priorities, socio-economic characteristics and built environmental characteristics. The sample yielded 29% ridesharing users, 30% non-users who indicated interested in future ridesharing, and 41% non-users that had no future ridesharing plans. Adelaide metropolitan neighborhoods with denser population distribution showed greater tendency to rideshare possibly due to issues relating to parking and congestion. The sample of participants above 40 years of age expressed low willingness to rideshare. A situation that can be attributed to the lower levels of digital literacy obtainable within that demography.

D. USE CASES FOR RIDESHARING AND CROWDSOURCING FOR CITIES IN CHINA

The authors in [130] conducted a case study utilizing real-world dynamic ridesharing dataset based on DiDi (a ridesharing application) order data and land use GIS data of Hangzhou, China. Identification of traveler's choice regarding ride-sourcing in this work is treated as a classification problem in which supervised learning is adopted in problem solution. Multiple cases involving datasets that qualify as training data are used to fit the intended BSTF model design criteria. Also, some other state-of-the-art machine learning models such as the Bayesian Supervised Learning Tensor Factorization (BSTF) are engaged in creating a robust analysis of traveler preferences. The authors highlight the benefit of overcoming the complexity of high-order relationships among variables offered by BSTF alongside its applicability with Latent Class (LC) variables to capturing hidden preferences for travelers. The performance data is utilized applying BSTF and benchmarked against some machine learning models. For this research, the conditional interference (DT) model, naive Bayesian (NB) model, the basic neural network, the random forest model and support vector machine (SVM) model were applied. The comparison offers a basis for determining its classification efficiency in ridesharing mobility pattern analysis. The additional utilization of latent LC variables introduces underlying conditional probabilistic relationships, hence providing predictability and insight into travelers' preferences. The LC variables are further able to provide alternative means of interpreting nonlinear relationships between independent and dependent variable.

A two-stage process of structured learning was applied with stage one yielding five key variables (distance, waiting_time, vehicle_time, O_metro and O_shop) that showed significant probabilistic relationship with the service type. In stage two, variables "O_metro" and "O_shop" are grouped and have a single LC variable. The variables "O_metro", "O_shop" and distance are known to the travelers before journey time. There was also the possibility for waiting_time to be identified pre-trip based on its dependence on the ride-sharing platform's matching time and pickup time. The training data was used to develop the machine learning models by establishing four size variations of training data (i.e., 10%, 20%, 50%, and 80%). The receiver operating characteristic (ROC) curve which provides visual reference of diagnostic ability measurements for each classification model was applied to the BSTF model, the DT model, and the RF model for training data size 80%. The results established higher performance in BSTF models with respect to overcoming classification errors. The classification accuracy was found to increase in all models with increased training data sizes with the Random Forests model performing closest to the BSTF model and closely followed by the conditional interference model in all four cases.

The authors in [131] proposed a ridesharing architecture termed CountryRoads, unique for its 'one-shot low-information ridesharing system', which is capable of addressing shortfall is the transport system that exist within periods of the Chinese Spring Festival travel season. The proposed system is expected to offer a large-scale ridesharing system designed with the early objective of reducing the surge of homeward-bound persons during the Chunyun period in China. A limitation of the CountryRoads application is its design restricting considerations to one-to-one matching. A situation where one driver can only be matched to one passenger. The initial deployment of the ride-sharing application was subject to challenges relating to difficulties in establishing user credit that promotes trust between drivers and passengers. This was due to its irregular use resulting from its exclusive deployment during spring festivals. There were also problems relating to user loyalty as many users were discovered to utilize it as a backup option to already existing public transportation bookings. Finally, there was also concerns regarding the socio-economic class of individuals that could benefit most from the ridesharing arrangements and their interaction with the technology that would support the application. Solutions to the latter challenge was proffered through establishment of text messaging facilities to support deployments on Android and IOS digital platforms.

Three main modules are used in the design of the CountryRoads system: the user interface module, the matching module, and the notification module. User identification was tied to user phone numbers creating a flexible identification means. Natural language processing technology was utilized by the SMS platform to extract the route information by matching input with a dictionary containing all 361 city names in China. The adoption of SMS interface promoted the inclusion of basic phone users of lower-income status but introduced complexities relating to entering information in the absence of field labels and text boxes which increase margins for human error. The transmission of visual media information eliminated existing limitations to information types that can be transmitted. Results from surveys conducted revealed that addition of certain value-added services such as increased volume of driver and passenger information, insurance for both parties, influenced willingness of users to sign up for rides.

At the same time, gender seemed to have slight impact on likelihood of ride-sharing confirmation. Most users indicated their willingness to split fuel cost and toll charges with drivers. CountryRoad ridesharing offered greater flexibility in terms of scheduling and deviation from original route than conventional public transportation. It was also discovered that most riders preferred direct matches rather than multiple matches.

The authors in [132] argues that the depth of query from previous research has not established conclusively the effect of ridesharing on emission control. Their research proposes the need for further research to prove the extent of emission reduction obtainable from large-scale ride sharing as opposed to the utilization of occasional orders. Also, there is an attempt to establish the upper bound estimate of ridesharing's environmental benefits considering travelers' critical requirements and optimization models. Finally, there is a consideration of effects of speed fluctuations and ridesharing's speed acceleration on the emission in ridesharing scenarios. Utilizing data gathered from daily taxi trips in Shanghai as a heuristic for ridesharing demand, optimal matching of rides using different optimization criteria is estimated. Emission reduction through ridesharing is analyzed in four steps. First an inference of Origin-Destination pairs from data obtained from the taxis is obtained where an assumption is made that all taxis from original destination are willing to pool. This is then combined with original traffic speed on each road segment obtainable through taxi trajectory data. Combining this information and analyzing using the COPERT III model which evaluates emissions based on cold starts, hot starts, and evaporative emissions. The shareability network approach forms the major foundations for the research methodology in which every node represents a single trip and links between nodes depict routes.

Two scenarios namely the oracle and online scenarios are developed to evaluate the ridesharing benefits obtainable within the constraints of the model. These two scenarios are considered alongside original emissions data to determine the obtainable ridesharing possibilities relating to commuter demographics. The results of the simulations yielded data showing ridesharing could significantly reduce traffic emissions and result in reduced fuel consumption in both scenarios. Results indicated further that it was possible to reduce emission by up to 20% as ridesharing increases in usages. Results of pollutant reduction showed differing levels of efficiency in the order NOx > CO > FC/CO2/PM2.5 > HC. First-order speed acceleration effect in ridesharing is found further reduced fuel consumption by 0.36–0.96% in oracle scenario and 0.34–0.74% in online scenarios. The author highlighted the Matthew Effect brought about by increased emission efficiency in greater polluting environment leading to two spatial patterns for ridesharing's environmental benefits: the first a monocentric and concentric structure and the second a pattern following the circular and radial trunk roads.

These two scenarios are adequately represented by the consideration of trips over specific geographical areas and mapping of road networks to create clear topological features. The significant emission generated by rideshares on off roads was also highlighted in this work this creates a new consideration relating to environmental considerations. This is considered a considerably less disadvantage when measured against the 30-days cumulative increment of fuel consumption in same regions absent of ridesharing.

E. USE CASES FOR RIDESHARING AND CROWDSOURCING FOR CITIES IN BANGLADESH

The authors in [133] conducted a study with sixty research participants to evaluate the usability of ridesharing mobile applications in Bangladesh and explored issues relating to design limitations that had most effect on the growth of a ridesharing user community. Their evaluation was carried out on the ridesharing heuristic to identify limitations to the usage of ridesharing applications such as Uber, Pathao and Obhai. A twofold study was carried out as part of the research method. The first involved expert inspection to determine software flaws and the other adopted a structured survey where base users were asked to provide feedback. Four steps were taken to achieve the research goals, First, the authors identified ridesharing applications available in Bangladesh. Second, they conducted study which centered around application specialists and base users each providing information within their sphere of knowledge. Third, questionnaires were issued to users with expected responses focused on level of engagement classified by gender, age, and profession. Finally, they analyzed all data obtained from the research using descriptive statistics as a tool to assess usability both from a technical and user standpoint. The process was designed to obtain suitable recommendations with the power to increase user engagement with ridesharing applications.

Issues relating to usability were identified within each application evaluated. On expert evaluation, it was discovered that Pathao offered a comparatively better user experience, while Uber had a more ergonomic, minimalistic design, and more advanced error handling process.

The study revealed a dominance of age-related user preferences where those that were aged below 30 constituted the major users of pathao. Those that were aged 31 and over were mostly Uber App users. Gender preferences revealed that uber was most prominent among both sexes, an observation that was credited to its superior handling of errors and efficient dispatch of rides. In measurement of user experience, in relation to satisfaction from rides, considerations of how easy the app features were to use and remember, Patho was considered the top performing application. Uber was considered the next best and Obhai third on the ranking. The Uber App was observed to have less bugs than Patho and Obhai which were locally developed applications. It was observed that despite its superior design, the Uber App lacked the versatility showed by the local apps in terms of payment options and integrations with local language interfaces. These formed the basis of usability advantage shown by apps such as Pathao among the Bengali community.

F. TAKE-HOME MESSAGE SUMMARY FOR USE CASES AND STUDIES FOR SMART CITIES

The survey works in this section have uncovered the following points and take-home messages for use cases and studies for smart cities:

- Most advanced cities around the world are faced with the key issues of traffic congestion, environmental pollution and fuel usage, and now consider ridesharing potential for more sustainable mobility in the foreseeable future. Given the potential and relative low cost of ridesharing, an increasing number of local authorities are incorporating it into their key policies to combat traffic congestion and reduce the emission of vehicle pollutants.
- More studies are needed to identity limitations and opportunities in specific cities to motivate strong interest from local authority policy makers to deploy ridesharing.
- Ridesharing not only promises to increase the sustainability of urban transportation, but also has the potential to increase cities' overall economic efficiency by generating jobs, avoiding wasteful vehicle ownership costs, and monetizing underused vehicles.

VII. APPLICATIONS USING RIDESHARING AND CROWDSOURCING

This section discusses seven applications utilizing ridesharing and/or crowdsourcing for urban and city environments: (1) Road conditions and monitoring; (2) Disaster and risk management; (3) Localization and sensing; (4) Package and food delivery; (5) Urban planning and heritage; (6) Smart living; (7) Marketing. Table 6 shows a summary of applications using ridesharing and crowdsourcing discussed in the sub-section.

A. ROAD CONDITIONS AND MONITORING

Monitoring road conditions is a critical issue in delivering smooth road infrastructure to travelers. The essence of monitoring road condition is to identify points that can compromise the transportation safety and driving comfort of road users such as potholes, defected pavements, bumps, etc. They also have an adverse effect on the operation of automobiles. Some of the earlier techniques employed for road monitoring included manual reportage of location of potholes and bumps on the route and the installation of monitoring hardware by the road side [134]. However, the whole cost of installing and maintaining this equipment reduces their sustainability. Currently, high-end vehicle is implanted with diverse sensors, for example, GPS, accelerometers that can identify road conditions as well as driving behavior. However, because of the cost of these technologies, they are only accessible in high-end vehicle models. Smart phones, on the other hand can be utilized as an alternative method to identify road conditions as they are nearly ubiquitous and accessible to travelers, and have various inherent sensory capabilities. These sensory capabilities of smart phones, together with their availability have been utilized by research in a crowdsourcing manner to develop more effective solution in this domain.

With smart phone-based sensing, Singh et al. [135] introduced a crowdsourcing technique for detecting road surface conditions. Their aim is to enhance the classification accuracy of identifying road surface condition utilizing dynamic time warping (DTW) because of its feature to spontaneously deal with time warps and varied speeds connected with time data. Also, its simplicity makes it best employed in resource-constrained devices as well as its training approach which is very fast compared to some other approaches like ANN, HMM, and SVM. The proposed technique enables informed decision on road maintenance and repair using real-time data. The suggested technique achieved detection accuracy and efficiency rate of 88.89% and 88.66% for bumps and potholes respectively.

Staniek [136] designed a road condition tool (RCT) using data crowdsourced from road users' smart phones. The tool identifies and assesses defects in road pavements through the analysis of vehicle motion dynamics in the road network. Road users' smartphones equipped with the RCT mobile application installed in onboard road users collects data about linear acceleration, speed, and vehicle motion, and transmits them to the RCT server database. The data is computed using the integrated time and location standard, and the road pavement condition evaluation index is approximated for fixed 10-meter-long measuring portions. The system allows for continuous wide monitoring of road infrastructure condition through multiple road transportation system users.

TABLE 6. Summary of applications using ridesharing and crowdsourcing.

Focus area	Work contributions	References
Road Conditions and Monitoring	Crowdsourcing technique for detecting road surface conditions	[135]
	Road condition tool (RCT) using data crowdsourced from smart phones	[136]
	Framework to model ridesharing and transit door-to-door services	[137]
Disaster and Risk Management	Mobile crowdsourcing tool (CrowdEIM) that utilize WeChat for reporting emergency information	[138]
	Crowdsourcing and crowdsensing data in smart city for humanitarian assistance and disaster recovery	[141]
	Crowdsourcing and participatory sensing to collaboratively publish emergency incidents	[142]
Localisation and Sensing	Crowd sourcing-based indoor mapping solutions	[143]
	System architecture for WiFi smartphone sensing	[144]
Package and Food Delivery	Crowdsourcing integrated transportation (CIT) framework that uses space created as passengers drop off to move packages	[160]
	City-wide package distribution framework leveraging crowdsourcing (CPTS)	[161]
	Network application for delivering food (FoodNet) employing spatial crowdsourcing	[162]
	Mathematical models for quantitative evaluation of crowdsourced delivery modes	[163]
Urban Planning and Heritage	Bibliometric study of current research for implementing crowdsourcing in urban planning	[166]
	Identified external stakeholder's role and flow of information for urban crowdsourcing process	[167]
	Characterization on crowdsourcing platforms in urban planning	[168]
Smart Living	Smart city-based system architecture (EasyGo) that offer personalized navigation for disabled	[171]
Marketing	Smart marketing technique that uses crowdsourcing mobile data to assess crowd flow	[175]
	Crowdsourced mobile data to aid market planners to plan for customer preferences and grow revenue	[174]

Li et al. [137] conducted a study on recent crowdsourcing techniques by analyzing driving jerks to detect high risk high way section. Driving jerks are sudden changes in acceleration that have been linked to increased traffic dangers. In their study, the authors equipped participant vehicles with a GPS unit and collected driving data at a rate of three hertz (Hz) for a period of 21 days. Examples of data collected includes latitude, altitude, longitude, speed, universal time code and date, heading as well as the number of utilized satellites. Following the data collection, each participants' dataset was divided into distinct trips, and plotted, to reduce noise and check for errors. In the second step, individual unique risky road portions were identified by grouping each participant's jerk spots spatially into clusters. The individual unique risky portions of all participants were further spatially merged with the testing sections of their study sites to calculate what number of time different users reported each road sections as a risky location. Their investigation hypothesized that when a road section is reported by several participants as a risky section with jerks' clusters observed on it, the section will be classified as a high-risk road section.

B. DISASTER AND RISK MANAGEMENT

Natural and man-made disasters are common emergency occurrences that cause loss of lives and properties in our society. Following the event of a disaster, emergency management agencies (EMAs), people as well as the whole society need a vast amount of reliable emergency information (EI) for effective decision making. As a result, good emergency information management (EIM) is critical in emergency responses. Considering the advancement of current ICTs, particularly the popularity of online social media and massively used smart phones, the general public will be able to easily and swiftly engage in the EIM. Assigning crowdsourcing tasks for some EIM to the general public and proactively exploiting the shared intelligence of the crowd, particularly the ones at the scene of an emergency, has yielded impressive benefits in emergency management practice [138], [139], [140].

Shen et al. [138] developed a mobile crowdsourcing tool named CrowdEIM that leverage WeChat official Account Platform for reporting emergency information. The authors conducted formative research to assist in designing and assessing their graphical model. They also applied a summative assessment to examine the performance as well as the usability of the implementable prototype. According to their results, EIM crowdsourcing tools utilizing mobile social media platforms hold high prospect to successfully spread and deliver more precise and intelligent emergency information, noting that only easy-to-use tools can be generally adopted in emergency situations. The CrowdEIM is limited to the WeChat platform, however, it promises to provide some useful recommendations to emergency management workers as well as aid in the exploration of further potentials for the utilization of mobile social media in the course of emergencies.

Pradhan et al. [141] examined and suggested a technique for connecting to and exploiting crowdsourcing and crowd sensing data in a smart city context to aid in effective humanitarian assistance and disaster recovery (HADR) operations. Their method considered how to utilize the ICT assets of citizens and responder agents to contribute situational awareness (SA) data for HADR operations in a disaster situation where the essential infrastructure of a smart city may be jeopardized. The mechanism allows end-user applications to transmit data to either edge devices or cloud servers. Edge computing helped to speed up HADR procedure by choosing and filtering useful information that may be broadcasted based on application areas. Edge nodes can further share useful information with upper levels devices like the centralized server to further process the information to create a common SA that participating HADR agencies can share. Based on the useful information circulated, emergency personnel and relief material can be transported to disaster location.

Jilani et al. [142] proposed a solution based on crowdsourcing which employ participatory sensing to enable numerous smartphone users to collaboratively publish emergency incidents. The system allows volunteers in the scene of an emergency to quickly send an alarm notification to emergency responders including critical information such as geographical coordinates, nature of occurrence, and number of casualties. The information is processed by the system, and an alert, together with improved route data, is issued to ambulances and other emergency responders. The results of their experiment revealed that the proposed framework is effective for practical deployment in future smart cities.

C. LOCALISATION AND SENSING

Location awareness has become increasingly important in many growing fields. An indoor map is a critical component of indoor location-based services (ILBS). Conventional indoor mapping approaches, on the other hand, are time-consuming. The evolution of smart phones provides excellent prospects for promising applications such as crowdsourcing-based indoor mapping because of its low cost and versatility. Many solutions based on smartphones for crowdsourcing-based indoor mapping have been proposed over the last decades.

Zhou et al. [143] provides a systematic study of several solution that have been developed. Their study classified indoor mapping process based on the level of map construction, and focused on two crucial processes; geospatial element acquisition and indoor map construction, and offered cutting-edge solutions on both areas. The authors further investigated crowd sourcing-based indoor mapping solutions and classified them as semantic maps landmark-based or grid-based. The study also compared the solutions in respect to sensors, experimental environment, participation, reported accuracy and output, in addition to the concepts, benefits and problems. Finally, they developed a measurable performance criterion for evaluating crowdsourcing-based indoor solution. From their result, the authors hypothesized that the unavailability of uniform comparison criteria, incentive mechanism and datasets are the primary constraints limiting the adoption of crowdsourcing-based indoor mapping.

Wu et al. [144] proposed a WiFi sensing system for a smart city that enable smartphone users to connect and provide network quality as well as exact locations of connected

WiFi hotspots to assist others in connecting to improved WiFi hotspots. The system integrated an endorsement network that allow users contribute reviews of WiFi hotspots as well as opinions about published data to ensure trust. Users can also endorse others who contribute reliable reviews of WiFi hotspots, forming an endorsement network. The system further evaluates user trustworthiness using the number of reviews they submitted and the endorsement they acquired. The system is deployed as a mobile application for mobile devices (e.g., smart phones) that gathers crowdsourced WiFi data and creates directional endorsement linkages between users.

D. PACKAGE AND FOOD DELIVERY

Customers are increasingly preferring online purchasing due to rising living standards and the convenience of doing so. Online retail turnovers of tangible products in the United States totaled 501 billion USD in 2018 and are expected to exceed 740 billion USD in 2023 [145]. Also in China, e-commerce revenue is estimated to reach 1095.5 billion USD by 2023 [146]. The increasing rise in online retailers, creates a high request for parcel delivery services, necessitating the long-term promotion of the logistics business. However, the efforts to deliver this enormous quantity of packages contributes to a rise in traffic congestion, resource utilization as well as environmental pollution (such as carbon emission), particularly during high traffic volume [147]. As a result, cities are seeking for tools and strategies to ensure systematic and proficient city transportation for commuters as well as packages. Several approaches have been used to explore the underutilized capacity of transportation technologies to minimize the unwanted carbon emissions and resource utilization and relieve traffic congestion resulting from dedicated package distribution transportation systems. The first type of approach centered on mixed logistics, where different types of vehicles (e.g., trucks, city freighter, micro aerial vehicles) are used to effectively complete the package deliveries. Some works, using the mixed logistic approach may be sighted in [148], [149], [150], and [151].

The second type of approach utilizes crowdsourced delivery in which package delivery jobs are freely and voluntarily outsourced to general crowdsourced network. Some studies that utilized this approach considered giving packages hitchhiking ride using taxi [147] and personal cars [152], while others propose to drivers to take as many as package delivery request in a single journey [153]. The third type of approach make use of the potentials of shared package together with passenger transit system [154], where Personal Rapid Transit (PRT) and Freight Rapid Transit (FRT) work together to meet transportation needs. This approach is utilized in the work of [155].

There has been a growing interest in resolving the package delivery problem through the use of various transportation technologies. For instance, personal cars [152], taxis [147] and unmanned aerial vehicles [156]. However, to provide a reasonable solution to the package delivery problem from the overall view and realize a whole benefit, studies using public transportation systems (PTSs) have shown great competence. The PTS, as a city infrastructure, is stable, time-planned, and cost-effective and widely covered [157]. Furthermore, it has a large amount of underutilized capacity during off-peak hours, which raises the possibility of capacity sharing between passengers and packages [158]. Cheng et al. [159] proposed a framework for Same-day Package Distribution employing Crowdsourced Public Transportation System termed SPDCP problem. Their work focused on devising a system that utilizes the fewest number of continuous bus/subway journeys in a manner that their underutilized capacity will be adequate for delivering a given set of packages while maintaining the quality of passenger experience (QoPE). However, such design goal faces the challenge of correctly computing the number of underutilized capacities for each journey between two nearby stations, and allocating empty space of each journey for package deliveries while maintaining QoPE. To address the challenges, the authors, first introduced the Passenger Transit Model which calculates the number of travelers throughout each journey to determine the space of vacant seats at each journey, which signifies the equivalent underutilized capacity. Secondly, they designed a Minimum Limitation Delivery method (MLD) that only uses the fewest number of underutilized capacities during the entire journey to accept packages, ensuring QoPE. They further constructed an Adaptive Limitation Delivery method (ALD) technique which stacks maximum parcels till the number of parcels stacked, in principle, fill the free space. The results of the experiment suggest that both MLD and ALD can efficiently distribute parcels.

Chen et al. [160] constructed a framework termed as crowdsourcing integrated transportation (CIT) that uses the space created as driver drop off passengers to move packages, allowing more transportation demands to be satisfied with minimum vehicles and drivers. The CIT framework is basically composed of three modules that includes crowdsourced resources, package delivery jobs and an Internet platform. Dedicated requests are sent to the crowdsourced resources to transport people from their point of origin to their point of destinations and at the same time offering hitching rides, utilizing the unused capacity to accomplish the package delivery job. The framework allows real-time location and time information regarding passenger flows and package flows in fine resolution to be easily collected and disseminated, giving ample data sources to tackle the problem of optimizing passenger flow and integrating parcel flow. The data flow received, together with the embedded intelligent algorithms are utilized by the online platform component to connect the crowdsourced resources and the packaged delivery job module, and then translates the data into decision. The online platform also enables the transfer of money from the senders of package to crowdsourced drivers as incentive after completing jobs.

Cheng et al. [161] presented a framework for implementing the city-wide package distribution leveraging crowdsourced

PTSs (CPTS), termed the CPDCP problem. The framework focused on leveraging the underutilized spaces of CPTS vehicles to ecologically and economically distribute packages to their last destination. For any given set of packages, the framework employs integer linear programming (ILP) techniques to mathematically formulate the problem and suggested an effective heuristic solution to the PN-hard problem. It can apply the model for a single bus route into the entire traffic network taking in to account transfers between any two bus routes. The evaluation of the method utilizing Changsha simulation in realistic settings revealed that the proposed method performed package delivery jobs more effectively and efficiently.

Liu et al. [162] designed a network for delivering food termed (FoodNet), employing spatial crowdsourcing to study the use of city taxis in on-demand take-out food delivering. The authors studied two Online Takeout Ordering and Delivery (OTOD) problems under various circumstances: (1) Opportunistic OTOD, where food is delivered opportunistically by taxis while transporting travelers, with the aim to minimize the number of participating drivers. (2) Dedicated – OTOD, where taxis are devoted to delivering food without picking up passengers with the goal to reduce the number of selected taxis as well as the overall traveling distance to cut costs. For their study, the authors proposed a two-stage strategy that employs a construction algorithm and the Adaptive Large Neighborhood Search (ALNS) algorithm in accordance with simulated annealing. The results of their experiment conducted in the city of Chengdu, China using real-world datasets revealed that the suggested algorithms completed food delivery service with a smaller number of taxis in the allotted time more effectively and efficiently than baselines.

As crowdsourced delivery continues to gain maturity, together with the intense competition among platforms, evaluating various crowdsourced modes for city package delivery has attracted the attention of researchers. Zhen et al. [163] presented six mathematical models for a quantitative evaluation of various crowdsourced delivery operation modes comprising of the grabbing mode, assignment mode, two tasks assignment mode, bonus mode, task cancellation mode, and mixed bonus cancellation mode, to assist crowdsourced businesses in making informed decisions. The results of their experiment showed that the assignment mode has a higher economic value in terms of firm earnings, and therefore is recommended for crowdsourcing business rather than the grabbing mode. The study also found that the benefit of bonus mode is relatively little. Furthermore, the authors recommend that firms should implement a mixed bonus-cancellation operation approach in order to attract clients.

E. URBAN PLANNING AND HERITAGE

The two keys factors that contribute to successful urban planning is public participation and information collection. Proficient urban planners have noted that for any policy and development plan to be properly implemented, adequate effort is needed to ensure citizens' participation and information collection. Gathering information from multiple sources will allow reconciliation of issues for environment safety, social cohesiveness and the provision of democracy [164]. On the other hand, the growing urban population together with fast urbanization presents a number of issues to urban planners due to the fact that growth in population increases the volume of data that reflects how people behave in relevant activities and how connected urban systems perform. Dealing with these issues in the past few years has been challenging, because of lack of effective methods for collecting and processing massive amount of urban systems performance and human behavior related data [165]. Urban crowdsourcing presents a modern type of open innovation aimed towards the development of smart cities.

Liao et al. [166] conducted a bibliometric study of current research to determine the prospects of implementing crowdsourcing in urban planning. The authors developed a database and list of keywords using peer-reviewed journal articles and then applied semantic analysis using the keyword lists to measure the co-occurrence frequencies of different terms in the articles and in turn build a semantic network. Their study identified crowdsourcing as a unique approach that the government can utilize to include public participation in urban planning in order to strengthen its capacity. Steils et al. [167] investigated and identified external stakeholder's role at each phase of the innovation process, as well as resultant dynamic flow of information that aid in the improvement of urban crowdsourcing process in the smart city solution's development. Their study recognized the primary stakeholders as the citizens, public authorities, and private and public corporation; as well as secondary stakeholders as universities, NGOs and consulting firms), depending on the level of complication of the innovation project. The results illustrated where they intervene in the four stages off urban crowdsourcing.

Chaves et al. [168] investigated how to characterize crowd work management on crowdsourcing platforms employed in urban planning with focus on quality of work. The result of their work showed that task definition and the user interface are closely connected to crowdsourcing approaches and influence how citizens participate in the urban planning process. D'Angelo et al. [169] employed crowdsourcing to build the database of digital materials (including photos, videos, and documents) necessary for making 3D models of cultural assets at low cost and with a short development time. This method enables tourists and inhabitants to contribute in the process of preserving cultural assets, growing the resilience of the cities.

F. SMART LIVING

Societies are becoming smarter as a result of increased development and widespread use of smartphones. By exploiting the increasing mobile device capabilities, for example processing power, diverse type of sensors, and numerous radios, a plethora of unique mobile applications may be encouraged for the daily lives of people, laying the basis for context-aware mobile applications [170]. Many researchers have leveraged crowdsourcing to generate large amount of data to develop context-aware solutions to enhance smart living. Panta et al. [171] designed smart city-based system architecture termed EasyGo that offer personalized navigation solutions for mobility impaired individuals depending on their preferences. EasyGo as a user enabled crowdsourcing platform, aims to provide for the collection of data on city's facilities and barriers for disabled persons and analyze the data to extract useful information. It then utilizes the facilities and barrier information to offer custom navigation and routing. The system further creates a database of disability-associated urban components and makes it available to all stakeholders as open access.

Wang et al. [172] developed a smart alarm sound recommendation system that works with smartphones to give smart alarm sounds by taking in account not just given information for example sleep pattern but also context information like social information and weather. The system coordinates sensing data gathered through smartphone sensors and integrates it with cloud computing to recommend favorite alarm sounds. To achieve this, the authors proposed a KNN- based technique for mapping alarm sounds to Arousal-Valance emotional states that successfully identify appropriate and customized sounds. When compared to typical alarm sound transmission systems, experimental data reveal that the proposed approach can improve people's emotional modes by roughly 10.73%. Marques and Pitarma [173] designed a mobile crowdsourcing solution named iNoiseMapping, for environmental noise monitoring. The results obtained from their analysis revealed that mobile crowdsourcing offers several improved features for environmental noise supervision and analytics.

G. MARKETING

With the progressive growth of smart cities, an increasing number of IoT objects are installed, generating vast amounts of data. Such devices are great means for data crowdsourcing, whether they are fixed or mobile. Portable and wearable devices, for example smart phones attract a lot of interest from market analysts since they can readily reflect consumer's behavior. Understanding consumer preference will enable marketers identify potential consumers. Utilizing Crowdsourced mobile data will aid market planners to plan for customer preferences, and advertisement, and grow revenue [174]. Chen and Ji [175] designed a smart marketing technique that uses crowdsourcing mobile data to assess crowd flow for geo-conquesting. The system aimed at enabling marketers and mall manager identify hotspots, large crowd flows; and passage flows in shopping centers and consequently adjust rental cost for retailers, digital advertising boards and traffic-flow design. The system receives user trial as input and produces a heat map and identified crowd flow as outputs. The system introduced local longest common subsequence-based (LLCS-based) clustering employing a distributed approach to detect crowd-flow to improve computing performance. When a sequence is introduced into the system, the dispatcher initially distributes it to a machine in one of the computer clusters based on the computational load.

Following that, the chosen machine executes an operation in the trajectory projection unit to map individual coordinates onto the layout map's associated blocks. As a result, all blocks will contain a segment or multiple segments of the whole sequence. After trajectory projection, the system categorized the trial segments contained in each block utilizing the suggested LLCS-based clustering method to form crowd flows. Following that, the system further divides each block into cells whereupon the trajectory directions are quantized to obtain information from the trials in the blocks. The system then calculates the number of in-trials and out-trails to create transition possibilities between blocks. The system may in addition get the block's visiting frequencies, which results in a heat map.

Many companies have deployed crowdsourcing from the marketing perspective in several projects such as market research, communication, new product development and testing, innovative ideas development and others. According to Gatautis and Vitkauskaite [176], Facebook used crowdsourcing since the year 2008 to create various versions of its site. The company claimed that utilizing the wisdom of the crowd enabled them to provide site versions that are well suited for local cultures. Minted (an American e-commerce company) employed crowdsourcing to obtain product designs from independent artists and sell the designs as fine items like stationary, wall art and decorations for homes, special occasions, and holidays. Clickadvisor also deploy crowdsourcing to obtain product reviews, decisions and concepts from consumers who act as brand advisors and utilizes advice on how the brand can be improved for research services. The findings of such customer research can be utilized to identify unmet customer needs, inform marketing decisions, and optimize innovative concepts and marketing campaign ideas. Furthermore, many businesses use Idea Bounty crowdsourcing platform to crowdsource creative ideas and marketing solutions from registered creative idea generators willing to take on challenging client briefs. Businesses offer monetary rewards in exchange for the best ideas that they intend to implement. FNB, The World Wildlife Fund, Unilever, Chevrolet, The Financial Times, and South African Breweries are among the brands that have collaborated with Idea Bounty [177].

H. TAKE-HOME MESSAGE SUMMARY FOR APPLICATIONS USING RIDESHARING AND CROWDSOURCING

The survey works in this section have uncovered the following points and take-home messages for applications using ridesharing and crowdsourcing:

- The development of mobile connected technology and public interest in affordable and environment-friendly services are driving the adoption of sharing economic

and collaborative systems in many application areas. The work of Pradhan et al. [141] shows that in the transportation sector, sharing economic and collaborative systems have gained attraction with ridesharing and crowdsourcing services implemented for several applications.
- The convergence of ridesharing and crowdsourcing systems offers the benefits of generating and processing massive amount of data, enabling fast and on-time decision making.
- Some research efforts have been made to harness these benefits in applications where real-time data generation and processing are required for optimal service delivery

VIII. OPEN CHALLENGES AND FUTURE WORK

This section presents various open challenges encountered in ridesharing and crowdsourcing for smart cities. The challenges captured in this work include digital divide, quality of connection, privacy protection, energy consumption, service reliability and robust mechanisms.

A. DIGITAL DIVIDE

Beyond the challenges of navigating user interfaces on ridesharing applications, social factors such as the available level of digital education for certain sections of the demography with an emphasis on the aging populace will be needed to eliminate digital divide. Most of the solutions to ridesharing and crowdsourcing do not consider this aspect of the society, however it should be in mind that the solution to ridesharing and crowdsourcing is not just for the minor section of the society, and it should be easy to use for all users especially older ones and persons with disabilities.

B. QUALITY OF CONNECTION

Wu et al. [144] introduced a WiFi sensing mechanism that promotes quality connection and network for users by assisting others in connecting to the improved WiFi hotspots. This mechanism aids evaluation of trustworthiness within the network using the number of reviews and endorsement submitted by the users. It is deployed as a mobile application for mobile devices that gather crowdsourced WiFi data and creates directional endorsement linkages between users.

C. PRIVACY PROTECTION

Privacy is one of the most challenging issues in ridesharing and the most prominent concern for individuals who take part in ridesharing. Ridesharing application users have expressed concerns with sharing private information such as travel time and travelers' information with strangers [5]. Also, the mobile crowdsourcing platforms uses information of workers such as, location and environment information for task allocation which could improve the quality of service. However, if the platform is hacked, it may result in disclosure of private information. The authors in [114] developed a model that only permits dispensing of sensitive information to devices on network with trusted status. This limit potential users access to information on ride segment based on their intended direction of travel without divulging information on joint commuters' location thereby protecting privacy without a sacrifice of ridesharing functionality. Balancing the use of technology for crowdsourcing to ensure that personal data is protected is a fundamental challenge in ridesharing.

D. ENERGY CONSUMPTION

Energy consumption of mobile devices is another challenge in ridesharing and crowdsourcing for smart cities. Smart phones use in ridesharing and crowdsourcing consume large amount of energy due to it communication medium such as upload and download links. To solve this problem, information such as user preferences, skills, and reliability of intelligent distribution of mobile crowdsourcing tasks, should be utilized by the administrators [178]. The authors in [93] proposed an approach termed as cluster-first-route-second to handle large-scale scenarios containing thousands of participants (drivers and riders). In this approach, the large-scale and computationally challenging problem is resolved by first decomposing into smaller problems by clustering. The authors in [17] proposed a cloud-based approach for real-time city-scale taxi ridesharing. The system utilizes multiple servers to perform the administration, computation, and storage. Their approach utilized passenger smartphones to make the real-time ride requests and incorporated factors such as time, capacity, incentive mechanisms and monetary constraints into the models.

E. RELIABILITY OF SERVICE

Reliability of service is a behavioral challenge in ridesharing. In a situation where the driver and the passenger agree on a schedule for ridesharing, If the driver has an urgent appointment or emergency, the passenger may have no ridesharing options for the return journey, and this is unacceptable. Also, drivers may be required to modify schedule or wait for passenger due to passenger's poor perceptions of reliability. Poor perceptions of travel reliability remain a major concern [179]. To solve this challenge, there should be slight modification to ridesharing services to allow confirmation of shared rides by passengers some hours before the share ride time. For example, passengers should be able to confirm their rides in the evening before the morning. This will create some balance between the travel reliability and schedule flexibility for both driver and passengers.

F. ROBUST RIDESHARING MECHANISMS

Only few researchers have considered the aspect of complex requirements in ridesharing such as cancellation of trips, urgent requests, and uncertainty problem. These changes occur due to user personal reasons, unplanned event, unexpected events such as break down of vehicles and traffic congestion. However, these challenge affects ridesharing and crowdsourcing in smart cities and should be considered for future inclusion in feature descriptions.

IX. CONCLUSION

This paper has given a comprehensive survey of paradigms for ridesharing and (mobile) crowdsourcing for smart city transportation environments. The paper aims to serve as a useful reference and discussion on how these new paradigms can be applied to solve large-scale problems in smart city environments. The review has covered the various models and architectures for (dynamic) ridesharing and crowdsourcing. The paper has also given insights into the various techniques and approaches which have been utilized such as matching, clustering, pathfinding, routing, task scheduling, etc. algorithms. The review has discussed the social factors which need to be considered such as security, policy and pricing. Use cases and applications for smart cities have been given. The review has given a roadmap and taxonomy of various approaches and techniques including how AI and autonomous vehicular systems can be utilized to develop practical deployments and solutions for smart city environments. The review has also uncovered open challenges to which remains to be resolved and given recommendations for future work in the following areas: (1) Ridesharing and crowdsourcing for elderly and disabled people; (2) Privacy and data protection issues; (3) Energy efficiency considerations used for mobile devices; (4) Service reliability; and (5) Robust mechanisms for ridesharing and mobile crowdsourcing. A final note is on the limitation of the survey work covered in this paper. While authors have endeavored to cover the published works in major databases, there may be works in other archives (e.g., arXiv) which are not covered in the paper.

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