Effects of Shared Mobility on Transportation Systems

Subjects: Transportation Science & Technology
Contributor: Fatema Elwy , Raafat Aburukba , A. R. Al-Ali , Ahmad Al Nabulsi , Alaa Tarek , Ameen Ayub , Mariam Elsayeh

Shared mobility is one of the smart city applications in which traditional individually owned vehicles are transformed into shared and distributed ownership. Ensuring the safety of both drivers and riders is a fundamental requirement in shared mobility.

shared mobility | smart transportation | delivery services | smart cities | IoT

1. Introduction

Population growth around the globe introduced new transportation challenges. Shared mobility involves the convergence of novel digital platforms and innovative solutions, marking a departure from traditional individual ownership toward communal resource utilization. This transition is particularly evident in the transportation industry, where the quick uptake of shared mobility platforms has led to significant economic growth. As highlighted in [1], the sharing economy's prevalence within the mobility sector is projected to experience a compounded annual growth rate of 23% from 2013 to 2025. These platforms leverage technology to streamline the sharing of transportation resources.

The Internet of Things (IoT) plays a significant role in generating large amounts of data through sensors and allowing things such as shared mobility to be connected. Furthermore, cloud computing platforms support IoT in data collection and creating software services for data analysis.

In shared mobility systems, individuals or companies can offer their vehicles for others to use. The shared mobility activities include dynamic systems in which drivers and riders are matched through automated processes facilitated by shared mobility services.

2. Effects of Shared Mobility on Transportation Systems

Ride sharing involves the practice of offering drivers the chance to add extra passengers to existing car trips. Initially, ride-sharing platforms were websites used as public noticeboards where users could freely post and search for excursions, which were often grouped using keywords like cities. Through these tools, individuals might get in touch with one another and spontaneously plan collaborative trips [2]. These online platforms improved over time, gradually increasing the effectiveness of setting up carpooling arrangements by introducing a booking-based system for facilitating connections and coordinating shared journeys [3]. To facilitate the seamless connection between drivers and passengers, studies on ride-sharing algorithms focus on optimizing the count of driver–rider pairs to the maximum extent [4], minimizing the overall distance or travel time for drivers [5][6][7], or reducing the overall detour duration [8][9]. A recent study [10] has proposed a real-time ride-sharing system with dynamic temporal segmentation and anticipation-based migration. The framework showed improved commuter waiting times by up to 65% and raised frequencies of successful matches by 136.11% through proper parameter tweaking using formal modeling and practical methods.

Another application of shared mobility is micro-mobility services. Micro-mobility refers to the provision of mobility services via a fleet of small, low-speed vehicles (primarily bikes and e-scooters) for personal transportation in urban areas as an alternative to ride hailing, public transportation, or walking, where vehicles can be accessed by one person at a time and charged at a usage rate. Urban areas have the highest concentration of bike-sharing systems, which let people use traditional or electric bicycles whenever they need them from a network of dock-based stations or for short trips in places with good connectivity and a density of free-floating destinations based on GPS and mobile apps [1]. Studies on micro-mobility systems mainly focused on three areas: the difficulty in distributing bikes [11][12], the planning of vehicle routes [13][14], and prediction of bike-sharing demands [15][16]. To address the issue of bike-sharing distribution, [12] introduced a model based on an adaptive capacity-constrained K-centers clustering algorithm and mixed-integer nonlinear programming. The study [14] introduced a comprehensive framework employing reinforcement learning to address the vehicle routing problem. To reallocate resources for bike-sharing demands, [16] suggested a hierarchical model for predicting the number of rents/returns of each bike.

Due to the emergence of these shared mobility platforms among users, communities, and urban landscapes, safety issues around their use should be highly considered. The safety of passengers becomes a vital concern as people depend more and more on shared mobility services choices. Ensuring the secure operation of shared mobility systems mainly depends on monitoring the behavior of road users, especially bike and scooter riders, and minimizing the vulnerabilities they are exposed to on the road [17]. Specifically, most studies on ensuring bike/scooter rider safety focused on the use of smart helmets [18][19][20][21][22] or smart bikes [23][24][25] along with mobile applications [19][23][24][25] or cloud-based databases [22][25].

In the study [18], a helmet-integrated control system was presented with the goal of improving biker safety and lowering accidents, especially those with serious consequences. The proposed system enforced mandatory helmet wearing via a Radio-Frequency (RF) transmitter and receiver setup, ensuring compliance with the legal requirement of wearing a helmet. In [19], a smart helmet was implemented to prevent bike accidents caused by alcohol consumption and lack of helmet usage. Utilizing gas, infrared, vibration, and MEMS sensors, the proposed prototype detected alcohol levels, helmet usage, vehicle load, reckless driving, and accidents. The prototype included a PIC microcontroller, LCD display, and Android application, sending accident information via GPS to hospitals and providing alerts to riders in case of non-compliance. Similarly, [20] used gas sensors and infrared sensors along with a GSM/GPRS module to warn medical staff in emergency situations. The study [21] proposed a helmet-based system using a PIC microcontroller. The system used a force-sensitive resistor to detect helmet wearing, an activated buzzer for helmet reminders, and an LED that flashes when the speed sensor detects exceeding speed limits. The study in [23] proposed a smart bike system that incorporated an Android application on the smartphone for data transmission through the 4G network between the app and a cloud-based real-time database and a microcontroller for communication via Bluetooth 4.0 Low Energy (BLE) between sensors and the phone. The study used ultrasonic sensors to detect nearby vehicles and an inertial measurement unit to measure acceleration and angular velocities. A smart bike architecture, proposed by [24], integrated a microcontroller, an accelerometer/gyroscope module to monitor bike movements, and a GSM/GPRS module to collect the bike's location and send it over the cellular network to emergency contacts. The study in [25] used a similar system along with the use of MQTT protocol to transmit the collected data to a cloud-based database.

Several machine-learning approaches were used in the literature [26][27][28] to analyze sensor-collected data patterns in driving behavior that affect safety. An Artificial Neural Network (ANN) algorithm is proposed in [26] for detecting abnormal movements among motorcyclists. The study utilized smartphone accelerometer and gyroscopes sensors data. The ANN algorithm processed these collected data to make decisions. The system is trained to identify nine distinct types of movements, and it achieved detection with varying accuracies. On average, the ANN demonstrated an accuracy rate of 96.2%. The embedded sensors of smartphones are also utilized in [27] to identify four distinct driving activities among motorcyclists. The study evaluated various classifiers, with the random forest (RF) classifier achieving the highest accuracy of 86.51%.

Another system that deploys the random forest classifier based on mobile phone sensors data is introduced in [28]. This system, named the Vehicle mode-driving Activity Detection System, comprises two primary modules. The Vehicle mode Detection Module (VDM) is designed to determine the user's current mode of transportation (such as walking, biking, motorcycling, driving a car, or riding a bus) based on the smartphone's accelerometer input. The second module, referred to as the Activity Detection Module (ADM), is dedicated to recognizing four core driving activities by analyzing data from the smartphone's accelerometer, gyroscope, and magnetometer sensors. The system managed to achieve an average accuracy of 98.33% in identifying vehicle modes and an average accuracy of 98.95% in identifying the motorist movements.

This section provides a broad overview of the transformative effects of shared mobility on transportation systems, focusing on the shift away from traditional ownership paradigms and toward cooperative resource utilization [1]. The growth of ride-sharing services and other shared mobility platforms has sparked the creation of sophisticated algorithms that optimize interactions between drivers and passengers and boost the effectiveness of shared travel [2][3][4][5][6][7][8][9][10]. Research has not only focused on mobility sharing effects on urban transportation but also on distribution techniques, route optimization, and precise demand forecasting [11][12][13][14][15][16]. Safety concerns sparked creative solutions, such as smart helmets, smart bikes, and mobile applications intended to protect road users, as these platforms have grown in popularity [17][18][19][20][21][22][23][24]. In addition, machine-learning techniques have been used to identify accidents and categorize traffic irregularities using sensor-collected data [26][27][28]. These results highlight the complex interactions between shared mobility, technological development, and safety improvements in modern transportation paradigms.

References

1. Shaheen, S.A.; Martin, E.; Bansal, A. Peer-to-Peer (P2P) Carsharing: Understanding Early Markets, Social Dynamics, and Behavioral Impacts; Transportation Sustainability Research Center: UC Berkeley, CA, USA, 2018; Available online: https://escholarship.org/uc/item/7s8207tb (accessed on 30 August 2023).
2. Furuhata, M.; Dessouky, M.; Ordóñez, F.; Brunet, M.-E.; Wang, X.; Koenig, S. Ridesharing: The state-of-the-art and future directions. Transp. Res. Part B Methodol. 2013, 57, 28–46.
3. Guyader, H. No one rides for free! Three styles of collaborative consumption. J. Serv. Mark. 2018, 32, 692–714.
4. Santos, D.; Xavier, E. Dynamic Taxi and Ridesharing: A Framework and Heuristics for the Optimization Problem. In Proceedings of the Twenty-Third International Joint Conference on Artificial Intelligence, Beijing, China, 3–9 August 2013; pp. 2885–2891.
5. Huang, Y.; Bastani, F.; Jin, R.; Wang, X.S. Large Scale Real-Time Ridesharing with Service Guarantee on Road Networks. Proc. VLDB Endow. 2014, 7, 2017–2028.
6. Ma, S.; Zheng, Y.; Wolfson, O. T-Share: A Large-Scale Dynamic Taxi Ridesharing Service. In Proceedings of the 2013 IEEE 29th International Conference on Data Engineering (ICDE), Brisbane, QLD, Australia, 8–11 April 2013; pp. 410–421.
7. Ma, S.; Zheng, Y.; Wolfson, O. Real-Time City-Scale Taxi Ridesharing. IEEE Trans. Knowl. Data Eng. 2015, 27, 1782–1795.
8. Pelzer, D.; Xiao, J.; Zehe, D.; Lees, M.H.; Knoll, A.C.; Aydt, H. A Partition-Based Match Making Algorithm for Dynamic Ridesharing. IEEE Trans. Intell. Transp. Syst. 2015, 16, 2587–2598.
9. Schreieck, M.; Safetli, H.; Siddiqui, S.A.; Pflügler, C.; Wiesche, M.; Krcmar, H. A Matching Algorithm for Dynamic Ridesharing. Transp. Res. Procedia 2016, 19, 272–285.
10. Guo, Y.; Zhang, Y.; Boulaksil, Y. Real-Time Ride-Sharing Framework with Dynamic Timeframe and Anticipation-Based Migration. Eur. J. Oper. Res. 2021, 288, 810–828.
11. O’Mahony, E.; Shmoys, D. Data Analysis and Optimization for (Citi)Bike Sharing. In Proceedings of the AAAI Conference on Artificial Intelligence, Austin, TX, USA, 25–30 January 2015; Volume 29.
12. Liu, J.; Sun, L.; Chen, W.; Xiong, H. Rebalancing Bike Sharing Systems. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco, CA, USA, 13–17 August 2016.
13. Ritzinger, U.; Puchinger, J.; Hartl, R.F. A Survey on Dynamic and Stochastic Vehicle Routing Problems. Int. J. Prod. Res. 2015, 54, 215–231.

14. Nazari, M.; Oroojlooy, A.; Snyder, L.; Takac, M. Reinforcement Learning for Solving the Vehicle Routing Problem. Available online: https://proceedings.neurips.cc/paper/2018/hash/9fb4651c05b2ed70fba5afe0b039a550-Abstract.html (accessed on 30 August 2023).
15. Du, B.; Hu, X.; Sun, L.; Liu, J.; Qiao, Y.; Lv, W. Traffic Demand Prediction Based on Dynamic Transition Convolutional Neural Network. IEEE Trans. Intell. Transp. Syst. 2021, 22, 1237–1247.
16. Yang, J.; Guo, B.; Wang, Z.; Ma, Y. Hierarchical Prediction Based on Network-Representation-Learning-Enhanced Clustering for Bike-Sharing System in Smart City. IEEE Internet Things J. 2021, 8, 6416–6424.
17. Turoń, K.; Czech, P.; Tóth, J. Safety and Security Aspects in Shared Mobility Systems. Sci. J. Silesian Univ. Technol. Ser. Transp. 2019, 104, 169–175.
18. Agarwal, N.; Singh, A.K.; Singh, P.P.; Sahani Dfa, R. Smart helmet. Int. Res. J. Eng. Technol. 2015, 2, 19–22.
19. Jesudoss, A.; Vybhavi, R.; Anusha, B. Design of Smart Helmet for Accident Avoidance. In Proceedings of the 2019 International Conference on Communication and Signal Processing (ICCSP), Melmaruvathur, India, 4–6 April 2019; pp. 0774–0778.
20. Srithar, S.; Venkata Suvathe, V.S.; Vijay Pandi, S.; Mounisha, M. Implementation of Smart Secure System in Motorbike using Bluetooth Connectivity. Int. Res. J. Eng. Technol. 2019, 6, 4817–4821.
21. Mohd, A.; Madzhi, N.K.; Johari, J. Smart Helmet with Sensors for Accident Prevention. In Proceedings of the 2013 International Conference on Electrical, Electronics and System Engineering (ICEESE), Selangor, Malaysia, 4–5 December 2013; pp. 21–26.
22. Swathi, S.J.; Raj, S.; Devaraj, D. Microcontroller and Sensor Based Smart Biking System for Driver’s Safety. In Proceedings of the 2019 IEEE International Conference on Intelligent Techniques in Control, Optimization and Signal Processing (INCOS), Tamilnadu, India, 11–13 April 2019; pp. 1–5.
23. Lai, P.C.; Huang, H.Z.; Sheu, M.H.; Wu, C.M.; Le, J.T.; Chen, T.H. Bike Sensor System Design for Safety and Healthy Riding. In Proceedings of the 2018 IEEE International Conference on Consumer Electronics-Taiwan (ICCETW), Taichung, Taiwan, 19–21 May 2018; pp. 1–2.
24. Islam, M.M.; Ridwan, A.E.M.; Mary, M.M.; Siam, M.F.; Mumu, S.A.; Rana, S. Design and Implementation of a Smart Bike Accident Detection System. In Proceedings of the 2020 IEEE Region 10 Symposium (TENSYMP), Dhaka, Bangladesh, 5–7 June 2020; pp. 386–389.
25. Tashfia, S.S.; Islam, R.; Sultan, S.I.; Rahman, M.W.; Habib, A.; Pinky, L.Y. Intelligent Motorcycle Monitoring Scheme Using IoT with Expert System in Bangladesh. In Proceedings of the 2020 23rd International Conference on Computer and Information Technology (ICCIT), Dhaka, Bangladesh, 19–21 December 2020; pp. 1–6.

26. Nuswantoro, F.M.; Sudarsono, A.; Santoso, T.B. Abnormal Driving Detection Based on Accelerometer and Gyroscope Sensor on Smartphone using Artificial Neural Network (ANN) Algorithm. In Proceedings of the 2020 International Electronics Symposium (IES), Surabaya, Indonesia, 29–30 September 2020; pp. 356–363.
27. Raheel, A.; Ehatisham-ul-Haq, M.; Iqbal, A.; Ali, H.; Majid, M. Driving Activity Recognition of Motorcyclists Using Smartphone Sensor. In Proceedings of the International Conference on Intelligent Technologies and Applications INTAP 2019, Bahawalpur, Pakistan, 6–8 November 2019; pp. 684–694.
28. Lu, D.-N.; Nguyen, D.-N.; Nguyen, T.-H.; Nguyen, H.-N. Vehicle Mode and Driving Activity Detection Based on Analyzing Sensor Data of Smartphones. Sensors 2018, 18, 1036.