SAVs Mobility Services and PT

Subjects: Transportation
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Autonomous vehicles (AVs) represent the core technology that will revolutionize urban mobility in the future. AVs are considered upgraded versions of conventional vehicles that have high levels of automation to assist or replace human drivers. Shared autonomous vehicles (SAVs) is AVs used for the purpose of providing vehicle sharing services. When attempts are made to adopt AVs into shared and demand-responsive services, public transportation (PT) systems are affected, thereby creating changes in mode share. This could potentially create a difficult dilemma for many European and Asian cities that heavily rely on their public transportation systems.

Keywords: public transportation ; shared autonomous vehicles

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1. Background

Autonomous vehicles (*AV*s) represent the core technology that will revolutionize urban mobility in the future. *AV*s are considered upgraded versions of conventional vehicles that have high levels of automation to assist or replace human drivers. However, if we simply treat *AV*s as upgraded versions of vehicle control, the benefits of deploying expensive technology will be marginal, particularly in large urban road networks with high travel demands and limited space. Hence, recent studies have focused on the potential for operating *AV*s as urban mobility services, such as demand-responsive transit (DRT) and shared vehicles [1]. Numerous studies have attempted to assess the impacts of operating *AV*s for urban mobility services using various approaches, such as survey reports [2][3], economy-based analyses [4][5], and simulation models [6][7][8].

When attempts are made to adopt *AV*s into shared and demand-responsive services, public transportation (*PT*) systems are affected, thereby creating changes in mode share. This could potentially create a difficult dilemma for many European and Asian cities that heavily rely on their public transportation systems. To avoid future problems, the relationship between newly formed mobility services and *PT* systems should be analyzed. Extensive research has been conducted on DRT [9][10] to develop methods for evaluating DRT systems with flexible route services [11][12][13]. However, these studies have commonly compared flexible route services with existing *PT* systems, while considering *PT* as a competitor. Other studies attempted to develop methods for allowing the interaction of flexible route services with existing *PT* systems [14][15][16]. However, these works mostly did not include *AV*s or shared vehicles within their concepts. Recent studies have begun to focus on evaluating shared autonomous vehicle (*SAV*) operations in urban areas [8][17][18]. Nonetheless, their common perspective was that *PT* is a competitor and is to be replaced by *SAV*-based services in the future. However, for cities that heavily rely on *PT*, such as Seoul of South Korea, in which the modal portion of *PT* is higher than 60%, this scenario could potentially create various problems, including public debts from bankruptcy, traffic congestion from modal shift, and a lack of mobility for the poor. Nonetheless, there has been a lack of discussion regarding the impact of *SAV* operations on existing *PT* systems and the interactions between the two [19].

2. Agent-Based Simulations for Impact Analysis

Numerous studies have been conducted to anticipate the potential impacts of *SAV* operations, particularly in recent years. Various approaches have been proposed, and the use of agent-based simulations is one of the main branches in *SAV* impact analysis. Agent-based simulations have been broadly utilized because of their flexibility in designing experimental settings for various study purposes. Some simulations may be designed to analyze only local impacts on partial urban areas [20][21], or may be designed to analyze the impacts on large urban areas. Especially for the latter approach, the use of a multi-agent transport simulation (MATSim) [22] has been popular, because it has high applicability to large-scale urban areas, and it is high speed due to being based on mesoscopic traffic flow models; furthermore, the latter can also be used to obtain a sufficient level of detail by reflecting individual travelers' activity plans. The demand estimation in MATSim is usually performed based on individual agents' plans of movement between activity locations. The main differences from previous studies are the mode choice mechanisms of multi-agents. The mode is chosen by either discrete choice modeling [23] or utility scoring [24][25]. While using such a simulation toolkit, various studies have also differed in terms of evaluation targets. Some are more interested in the extents to which *SAV* operations can reduce traffic congestion in urban areas [26]; others are more interested in the changes in detailed travel behaviors within specified urban areas, such as vehicle kilometers traveled (VKT) [7][27] and passenger waiting times [28].

Several studies have designed their own simulations rather than using MATSim for various purposes. Some such studies involved analyzing the impacts of employing shared taxis in a large urban area. The common results of the related studies are that shared taxis reduce traffic congestion [29][30] and VKT [31] compared to the conventional taxi systems by reducing the fleet size. Others have tested the impacts of employing EVs in urban areas. These studies related to EVs for shared mobility services show that EVs may increase the VKT because of empty trips required for battery charging, but they can still reduce operational costs [32] and increase sustainability [33].

All the studies mentioned above used agent-based simulations for impact analysis of *SAV* operation from various perspectives. However, most of them considered the *SAV*s as a replacement for private vehicles and existing public transit. Discussions regarding the impacts of *SAV* operations on existing *PT* systems or the interaction between the two services are scarce.

3. City-Wide Impact Analysis

Most previous studies have analyzed the impacts of *SAV* operations at a large-scale urban level because of the anticipation of the city-wide deployment of *SAV*s. According to Narayanan et al. [34], city-wide impact analyses have been conducted from various perspectives, such as economic, urban traffic performance, and travelers' mode choice perspectives. In fact, all these studies can be seen as sustainability-related works on *AV*-based mobility services, since they all "attempt to understand and manage concomitant environmental, economic, and social issues" [35].

The usual method employed for city-wide economic analysis is to express the impacts in terms of cost. Based on an analytical calculation of the total trip distance and the required fleet size of autonomous taxis, Brownell and Kornhauser [4] estimated the cost per person, per day. Chen et al. [32] developed an agent-based simulation model of a hypothetical urban area and derived the operational cost per kilometer in an electric *SAV* environment using simulation tests. Ongel et al. [36] calculated the cost per passenger-km based on the analysis of various information sources for operational costs.

The results of previous studies are controversial in terms of urban traffic. Some studies have found that *SAV* operations can increase congestion in urban areas, particularly after peak hours because of the increased number of empty trips after providing services [37]. In contrast, the results of other studies indicate that congestion can be significantly reduced when the travel mode sharing level meets a certain value [29][30]. Similar results were obtained in VKT-based analysis. Some studies showed that there is an increase in VKT in the city-wide analysis because of empty vehicle trips [38][39]. Childress et al. [40] derived similar results; however, they also showed that there can be positive impacts when all vehicles become automated and shared.

Simulation-based analyses can be performed in terms of travelers' mode choices. Based on activity-based simulation results, Liu et al. [23] showed that private vehicle owners, particularly in rural areas, prefer *SAV*-based services. Another example of simulation-based analysis has shown that, if private vehicle usage is disabled, most travelers prefer to use *SAV*-based services rather than *PT* [6]. Survey-based analyses have also been conducted for the impacts on travelers' mode choices. The common result of such analyses is that conventional *PT* (or multimodal transit) users are positive about switching to *SAV*-based services; however, private vehicle owners are less likely to use *SAV*s [2][41]. Hence, the results of impact analyses on travelers' mode choices are still controversial.

In addition, there have been a few interesting studies analyzing the impacts on shared mobility cause by internal urban aspects, such as the accessibility of services influenced by demographic factors and transportation infrastructure [42]. There have also been a few studies on the impacts of external forces such as weather [43] and pandemics such as COVID-19 [44].

4. The Impact on Public Transit Systems

As described in the previous section, several existing studies have considered *PT* to be a competitor and an object to be replaced by *SAV*-based services in the future. However, it is difficult to expect that unmanned vehicles will completely take over existing systems in the future. Still, the adoption of *SAV*s will serve as a factor that continuously changes the shares of existing travel modes. Therefore, the impact of *SAV*-based services on existing *PT* systems or interactions between the two must be analyzed. Accordingly, Shen et al. [19] recently changed their ideal to *SAV* operations integrated with a *PT* system. They performed an agent-based simulation to evaluate an *SAV–PT* integrated system and suggested that replacing little-used bus routes with *SAV*s would significantly increase the efficiency of the integrated system. Subsequent studies have been conducted for further development of *PT–SAV* integration [45][46], and there is growing interest in this topic. The commonality of these recent studies was that they proposed integrated systems and then compared the results before and after applying the systems for testing the efficiency in terms of travelers' waiting times. However, they did not consider the detailed changes in the modal split ratio between *PT* and *SAV* when they interacted with each other in detail. Furthermore, the extent to which the interaction would reduce the number of private vehicles should also be considered in a city-wide analysis.

Therefore, the first objective of this study was to provide a simulation-based method to analyze the modal shift by local travelers between *PT* and *SAV* when the two modes interact with each other. Then, using the properties of the simulated results, the second objective was to propose a city-wide impact analysis method that can reflect the differences between urban types in terms of travel behaviors. The use of the combined approach of the two analyses (simulation and analytical methods) is a major difference between the current study and previous studies. Note that, in this study, we focus more on the impact of *SAV* operation on *PT* rather than evaluating the direct efficiency of the interaction system. Hence, we consider the following three criteria. The first is the matching ratio between service vehicles and passengers, which represents the service satisfaction of system users. The second is the mode choice ratio of travelers, which is closely associated with mobility service efficiency. The third is the rate of increase/decrease in the number of private vehicles, which is a major factor affecting urban congestion. The following section provides details of the analysis methods.

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