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Economic analysis of vehicle infrastructure cooperation for driving automation

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ABSTRACT

The current approach to driving automation has been primarily vehicle-centric. However, a vehicle-infrastructure cooperative approach, in which infrastructure and vehicles cooperate to perform the different driving tasks, may prevail in enabling automated driving. This paper conducts an economic analysis of vehicle infrastructure cooperation for automated driving. In doing so, we present a model that captures investment decisions in vehicle automation and infrastructure digitalization and their effect on travelers' purchase and travel decisions. Our analysis shows that, under certain conditions, equipping both infrastructure and vehicles is socially optimal. However, by analyzing strategic interactions between infrastructure support service providers and automakers, we show that lack of coordination between these two actors results in suboptimal investment in vehicle automation and infrastructure digitalization. Especially, when these two technologies are complementary, service providers are reluctant to invest in digital infrastructure and vehicle manufacturers tend to over equip their vehicles so as to avoid relying on infrastructure technology. Thus, we conclude by showing that better coordination between automakers and service providers – under the form of profit sharing – is welfare-improving and could potentially yield the socially optimal levels of automation and digitalization.

1. Introduction

In recent years, automated driving has steadily become one of the hottest topics in the technology space. Especially, automated vehicles (AV) have garnered increased attention and interest from companies and investors. From 2014 to 2018, investments related to automated vehicle technologies totaled \$80 billions (Karsten, 2017). Those investments come from sources ranging from institutional investors to car manufacturers and ride-hailing companies. For example, Uber's initial public offering documents reveal that, from 2016 to 2018, the company spent close to \$29 millions per month on research and development for automated vehicles (Chai, 2019). More recently, Amazon acquired self-driving car company Zoox for close to \$1 billion (Weise and Griffith, 2020). These trends underscore investors' beliefs that, despite their negative impact on some industries, automated driving technology will provide numerous revenue-generating avenues, increase productivity and profitability, and reduce the social and human cost of driving (Clements and Kockelman, 2017). However, to date, fully automated vehicle technology has failed to materialize (only Level 2 has been commercialized thus far by companies like Tesla and General Motors), and the enormous amount spent on research and development suggests that significant technological hurdles must be overcome before the automated age of transportation. Indeed, loosely speaking, drivers perform three tasks when driving: perception, planning and control. Across

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the industry the effort has been centered on enhancing vehicles to perform all the above tasks, which has been difficult: AVs' perception abilities are still sensitive to weather and lighting conditions (Zhu et al., 2017; Van Brummelen et al., 2018); *a priori* vehicle localization and mapping is not, as of yet, robust to infrastructure changes and simultaneous localization and mapping is subject to perception challenges (Van Brummelen et al., 2018); and algorithms for planning and decision making (e.g., for lane changing) are computationally burdensome for vehicles, thereby limiting their applicability to real-time decision making (Katrakazas et al., 2015; González et al., 2016; Dixit et al., 2018; Schwarting et al., 2018). Additionally, while AV adoption is low, AVs in traffic mixed with conventional vehicles may compromise traffic stream stability and throughput (Chen et al., 2017; Luo et al., 2019). While these are not insurmountable challenges, public tolerance for errors and mistakes may be thin, as demonstrated by the aftermath of recent deadly AV crashes and the reported reservation of a non-negligible segment of the population towards driving automation (Ge et al., 2017). Thus, some investors and companies are starting to question their commitment to AV technology since it is unclear when they will be able to recoup their investment or whether the increased spending is worth the potential gains: there simply is no clear timeline for the deployment and adoption of fully automated vehicles as companies seek to minimize safety risks (Metz and Griffith, 2020; Efrati, 2020).

Given the challenges inherent to this vehicle-centric approach, researchers, investors, and the public sector have realized that placing some sensors and algorithms on the infrastructure may be a more effective way to enable automated driving. Thus, researchers have devoted themselves to the design, modeling and assessment of sensor networks to aid with vehicle perception and planning (Rebsamen et al., 2012; Jun and Markel, 2017; Leone et al., 2017; Bieshaar et al., 2017; Eilbrecht et al., 2017; Reitberger et al., 2018; Jayaweera et al., 2019; Kong, 2020) and improve a number of traffic performance metrics (Dey et al., 2016; Xie and Wang, 2018; Yu et al., 2019; Yang et al., 2021). Public agencies also see the future of transportation as closely tied to a vehicle-infrastructure cooperative approach. CARMA, a program from the Federal Highway Administration (FHWA), seeks to encourage and accelerate the research and development of cooperative driving automation that involves vehicle and infrastructure cooperation (FHWA, 2021). The Michigan Department of Transportation is partnering with Cavnue – a company founded by Sidewalk Infrastructure Partners, which is funded by Alphabet and other capital providers – to implement a corridor between Detroit and Ann Arbor that provides digital information to support driving automation. In Europe, the European Road Transport Advisory Council (ERTRAC), a structure that seeks to encourage cooperation and investment in critical road transportation innovation, supports multiple projects related to infrastructure connectivity and cooperative systems (ERTRAC, 2019). In China, the market for smart cities solutions, grown out of the central government's decades long development plan, is estimated at ϖ.1 trillions. This includes, among other things, investment in automated vehicles and smart transportation infrastructure (Atha et al., 2020).

In the approach of vehicle-infrastructure cooperation for enabling driving automation, both the level of automation in the future fleet and the level of digitalization in the future infrastructure will be heterogeneous. Similar to the SAE classification for AVs, Carreras et al. (2018) recently proposed a scheme to classify the readiness of road infrastructure to support and guide AVs . In their classification, at Level A and B the infrastructure will support cooperative driving and perception while at Level C all dynamic and infrastructure information will be provided in digital form to AVs; conventional infrastructure will be at Level D and E. With infrastructure-vehicle cooperation, a Level 3 AV may achieve full automation on a Level A infrastructure. Moreover, the liability associated with automated driving can be shared among automakers, infrastructure providers, and/or a third-party player, which may substantially accelerate the diffusion of the AV technology. Additionally, the digitalization of infrastructure could provide revenue generating opportunities for service providers. Indeed, smart infrastructure will make the provision of digital services to users as well as the monetization of traffic data easier. Some even see digitalization as the doorway to new means of financing infrastructure through data rather than taxes (Adriaens, 2021).

While these prospects offered by the vehicle-infrastructure cooperative approach are interesting and exciting, they also raise several questions worth policymakers and private parties' attention. First, it is natural to ask whether such an approach to automated driving makes economic sense and whether it would be socially beneficial. Moreover, this vehicle-infrastructure cooperative approach will give rise to a new market for infrastructure support service provided by an infrastructure support service provider (ISSP) like Cavnue. It is therefore crucial to understand how this new actor will interact with both automakers and customers and how the resulting interactions will impact the provision of automation and digitalization.

Thus, the aim of the present work is twofold. First, we present a modeling framework to examine whether vehicle-infrastructure cooperation for enabling automated driving makes economic sense. Specifically, we investigate, from a societal perspective, the optimal allocation of investment between the on-board and infrastructure-based sensors. We show that, at the social optimum, the heterogeneous provision of digitalization and automation naturally arises from the heterogeneity in vehicle and road usage. Then, we analyze the outcome of strategic interactions between automakers and ISSPs. Our model especially highlights the negative effects of a lack of coordination between auto manufacturers and service providers on vehicle automation and infrastructure digitalization spending. To the best of our knowledge, this study is the first economic study on the joint provision of vehicle and infrastructure technology for enabling automated driving. Our results offer insights on infrastructure-assisted automated driving and provide both the public and private sectors with additional avenues for cooperation in developing and deploying smart infrastructure. The rest of the paper is organized as follows. Section 2 presents our model setting. Then, in Section 3, both the social optimum and the Nash equilibrium are derived and compared. We present in Section 4 a numerical example to illustrate our analysis, and then conclude in Section 5.

Table 1
Frequently used notations.

(a) Frequently used variables

Notation	Description
x_i	Vehicle automation level for users of type i
d_i	Number of users of type i
U_i	Utility of users of type i
p	Price per unit of automation level
z_k	Digitalization level for road group k
V_k	Traffic volume on road group k
l_k	Total road length for road group k
v_{ik}	Vehicle miles traveled (VMT) per day by users of type i on road group k
τ_k	fee per mile traveled on road k
π^c	Manufacturer profit
π^r	Service provider profit

(b) Frequently used parameters

Notation	Description
v_i	Daily VMT by users of type i
κ_c	Amortization parameter for vehicle purchase
κ_r	Amortization parameter for road investment

2. Setting

For the convenience of readers, frequently used notations are listed in Table 1.

We consider a setting with vehicle-infrastructure cooperative deployment of automated driving where sensors, edge-computing devices and intelligence can either reside on the vehicle or infrastructure side to perform various driving tasks. A car manufacturer produces vehicles of various levels of automation and prices them differently. A private automation service provider or ISSP like Cavnue equips roads, whose usage varies, with various types of sensors and devices to assist vehicles in sensing, perception planning and maneuver. To finance the digitalization of these roads, the ISSP will charge a service fee. Additionally, the ISSP will also benefit from the data collected from users' digital footprint on her roads. Such an infrastructure-vehicle cooperation may yield significant benefits for users: reduction in driving opportunity cost, increased safety, etc. The level of benefits will depend on the combination of the automation level of the vehicles that the users are riding and the digitalization level of the roads their vehicle is on. Thus, users are faced with two choices. On one hand, they must decide the automation level of the vehicle they purchase based on the car manufacturer's offerings. On the other hand, they must decide which roads to use to complete their trips based on the digitalization choices of the ISSP.

In our model, users are divided into I user groups based on their vehicle-miles traveled (VMT). While we could instead consider heterogeneity along other dimensions (such as willingness to pay), considering VMT heterogeneity allows us to directly connect customers' decisions regarding automation to road usage since the latter is the main channel through which ISSPs earn a profit from digitalization. Thus, within each group i, users are identical in all aspects, including in their VMT v_i. However, users' VMT differ across groups. The number of users in group i is d_i. In making their vehicle purchase decisions, users essentially decide the automation level of their car x_i based on the price per unit of automation p_i. Additionally, they take into account the allocation of their VMT across K different groups of road infrastructure equipped with a digitalization level z_k and of a total road length l_k. Using a given road k results in users paying a service fee τ_k per mile. We treat x_i and z_k as continuous variables in $[x_{min}, x_{max}]$ and $[z_{min}, z_{max}]$ respectively.

Users' travel benefit is captured by a function $f_k(x_i, z_k, V_k, v_{ik})$ where v_{ik} denotes the amount driven by a user of group i on road k, and $V_k = \frac{\sum_i v_{ik} \cdot d_i}{l_k}$ denotes the average traffic volume on road k. Thus, a user from group i chooses her automation level x_i and travel pattern $\boldsymbol{v}_i = \{v_{ik}\}_k$ to maximize her utility U_i given by:

$$U_i = \sum_k [f_k(x_i, z_k, V_k, v_{ik}) - \tau_k \cdot v_{ik}] - \kappa_c \cdot p_i \cdot x_i \tag{1}$$

where v_{ik} is daily VMT of user i on road group k; and κ_c is a term that amortizes vehicle purchase cost to daily costs. Using $f_{k,i}$ to denote the derivative of f_k with respect to its ith argument while $f_{k,ij}$ denotes the cross partial derivative of f_k with respect to its ith and jth arguments, we make the following assumptions.

Assumption 1. Our assumptions on utility are as follows:

A1.1 Utility strictly increases with automation and digitalization: $f_{k,1}, f_{k,2} > 0$.
A1.2 Users' utility strictly increases with their amount of travel: $f_{k,4} > 0$.
A1.3 Congestion strictly decreases a given user's utility: $f_{k,3} < 0$.
A1.4 Utility is strictly concave in automation, digitalization and individual miles traveled: $f_{k,11}, f_{k,22}, f_{k,44} < 0$.
A1.5 Utility is strictly concave in travel volume: $f_{k,33} < 0$.

Assumptions A1.1 and A.1.3 are readily understood. Assumption A1.2 captures the fact that users derive a positive benefit from traveling (be it for leisure, work, shopping etc.). Note that travel's intrinsic purpose is to complete tasks that improve utility. Assumptions A1.4 and A1.5 ensure concavity of the user maximization problem and are intuitive when we consider decreasing marginal utility of consumption.

Vehicles for different user groups are manufactured by a profit-maximizing firm that decides the price per unit of automation p_i for vehicles it produces. More importantly, the firm must decide how much to invest to expand its production capabilities to meet the demand for automation from each user group. We specify the manufacturer's profit function as follows:

$$\pi^c = \sum_i p_i \cdot x_i \cdot d_i - c_c(x_i, d_i) \tag{2}$$

where $c_c(\cdot,\cdot)$ is the automation-related manufacturing and R&D costs for a vehicle as a function of its automation level and the number of units produced.

Assumption 2. Our assumptions on the manufacturer's cost function are as follows:

- **A2.1** The cost function is strictly increasing in automation levels and increasing in the quantity of vehicles manufactured: $c_{c,1} > 0$ and $c_{c,2} \geq 0$.
- **A2.2** The cost function is strictly convex in automation level: $c_{c,11} > 0$.
- **A2.3** The cost function is concave in the quantity of vehicles manufactured: $c_{c,22} \leq 0$.

A2.2 indicates that achieving higher levels of automation becomes increasingly costly for the manufacturer. As detailed in Section 1, this forms one of the basis for our present inquiry. A2.3 indicates economies of scale in the manufacture of vehicles.

Lastly, we consider a profit-maximizing ISSP who is interested in digitizing roads to achieve cooperative perception, planning and control of AVs. Note that this private ISSP does not necessarily own these roads. Instead, it partners with the road owner, who is likely a public agency, and is responsible for constructing and maintaining the digital infrastructure. This ISSP thus decides how much to invest to equip each road group with digitalization level z_k. Additionally, she decides the service fee per mile τ_{ik} on each of her roads for each user group. More importantly, this digital infrastructure operator is able to harness some additional benefits for each mile driven on its road via, e.g., the revenue from data monetization and advertising. This non-pricing benefit per mile can be captured by a function $b_r(x_i, z_k, V_k)$ and the profit function for the service provider is given by:

$$\pi^r = \sum_k \sum_i d_i \cdot [\tau_{ik} + b_r(x_i, z_k, V_k)] \cdot v_{ik} - \kappa_r \cdot \sum_k c_r(z_k, l_k) \tag{3}$$

where κ_r is a term that amortizes the investment cost to daily costs, and $c_r(\cdot,\cdot)$ captures the digitalization-related investment and maintenance costs per road mile as a function of digitalization level. Our functional form assumptions are given below:

Assumption 3. Our assumptions on the ISSP's cost and benefit functions are as follows:

- **A3.1** The non-pricing benefit function is strictly increasing in automation and digitalization levels: $b_{r,1}$, $b_{r,2} > 0$.
- **A3.2** The non-pricing benefit function is strictly increasing in travel volume: $b_{r,3} > 0$.
- **A3.3** The non-pricing benefit function is strictly concave in automation and digitalization levels: $b_{r,11}, b_{r,22} < 0$.
- **A3.4** The cost function is strictly increasing and strictly convex in digitalization levels: $c_{r,1}, c_{r,11} < 0$.

In essence, higher digitalization and automation allow the ISSP to collect and provide more information to aid in maintenance, data monetization and other services (Assumption A3.1). Moreover, the company benefits from higher usage on its roads since this leads to more data collected for monetization purposes (Assumption A3.2). Buried in that latter assumption is also that the contribution of road usage to maintenance cost is negligible or always lower than its contribution to the non-pricing benefit. Thus, in essence, $b_r(\cdot,\cdot,\cdot)$ could be thought of as the *net* pricing-benefit. Lastly, the higher the digitalization level, the higher the installation and maintenance costs (Assumption A3.4). Indeed, sensors and digital infrastructure will require constant monitoring to ensure their proper operation and reduce the risk of cyber-attacks and other related issues.

3. Equilibrium analysis

3.1. Social optimum

In this section, we consider the case in which a social planner maximizes social surplus by choosing automation and digitalization levels, in addition to users' travel patterns. The social surplus maximization problem is given by:

$$\begin{aligned}
\max_{x_i, z_k, V_k, v_{ik}} \quad & \sum_i d_i \cdot \sum_k [f_k(x_i, z_k, V_k, v_{ik}) + b_r(x_i, z_k, V_k) \cdot v_{ik}] - \kappa_c \cdot \sum_i c_c(x_i, d_i) - \kappa_r \cdot \sum_k c_r(z_k, l_k) \\
\text{s.t.} \quad & \sum_k v_{ik} = v_i \quad \forall i \in I \quad \text{(VMT constraint for users of group } i\text{)} \\
& V_k \cdot l_k = \sum_i v_{ik} \cdot d_i \quad \forall k \in K \quad \text{(Flow conservation constraint on } k\text{)} \\
& v_{ik} \geq 0 \quad \forall k \in K,\ i \in I \quad \text{(Flow positivity constraint)}
\end{aligned} \tag{W}$$

where the social surplus is the sum of consumers' utilities, manufacturer's profits and service provider's profits. At optimality, assuming that $f_k(\cdot,\cdot,\cdot,\cdot)$ and $b_r(\cdot,\cdot,\cdot)$ are strictly concave so that the optimum is an interior point, we obtain:

$$\sum_k \left[f_{k,1}(x_i, z_k, V_k, v_{ik}) + b_{r,1}(x_i, z_k, V_k) \cdot v_{ik} \right] \cdot d_i = \kappa_c \cdot c_{c,1}(x_i, d_i) \quad \forall i \in I \tag{4a}$$

$$\sum_i \left[f_{k,2}(x_i, z_k, V_k, v_{ik}) + b_{r,2}(x_i, z_k, V_k) \cdot v_{ik} \right] \cdot d_i = \kappa_r \cdot c_{r,1}(z_k, l_k) \quad \forall k \in K \tag{4b}$$

$$\alpha_k + b_r(x_i, z_k, V_k) + f_{k,4}(x_i, z_k, V_k, v_{ik}) - \frac{\gamma_i}{d_i} \le 0 \quad \forall k \in K, \forall i \in I \tag{4c}$$

$$v_{ik} \cdot \left[\alpha_k + b_r(x_i, z_k, V_k) + f_{k,4}(x_i, z_k, V_k, v_{ik}) - \frac{\gamma_i}{d_i} \right] = 0 \quad \forall k \in K, \forall i \in I \tag{4d}$$

$$\sum_i \left[f_{k,3}(x_i, z_k, V_k, v_{ik}) + b_{r,3}(x_i, z_k, V_k) \cdot v_{ik} \right] \cdot d_i = \alpha_k \cdot l_k \quad \forall k \in K \tag{4e}$$

$$v_{ik} \ge 0 \quad \forall k \in K, \forall i \in I \tag{4f}$$

where γ_i is the Lagrangian multiplier associated with the ith VMT constraint; α_k is the Lagrangian multiplier associated with the kth flow conservation constraint. Eqs. (4c)–(4e) indicate that, for each user group, the marginal benefit per mile of each used road group is equal, and is more than or equal to the marginal benefit per mile of non-used road groups. From Eq. (4a), the marginal social benefit of automation for users of type i must equal the social marginal cost of providing these users with automation x_i. From Eq. (4b), the marginal social benefit of digitalization for roads of type k must equal the social marginal cost of equipping these roads with digitalization z_k. In other words, allocating some resources to the infrastructure is socially optimal under the assumption of strict concavity of the benefit functions and strict convexity of the cost functions.

This suggests that an infrastructure-vehicle cooperative approach to automated driving deserves more attention. As expected, the levels of automation and digitalization for user and road groups will be determined by equalizing their social marginal cost to their social marginal benefit. Thus, under a set of constraints (budgetary and political etc.), automation and digitalization technologies with a higher marginal return should be given priority. Moreover, because of different VMT and volume distributions and cost functions, the equilibrium will result in a heterogeneous provision of both automation and digitalization. As pointed out by previous research, those with higher VMT will likely benefit from and desire higher levels of automation (Hardman et al., 2019; Hardman, 2021). We now proceed to investigate strategic interactions between automakers and service providers and how such strategic interactions affect the allocation of resources.

3.2. Generalized Nash equilibrium

We now explore a case in which the car manufacturer and the service provider act independently from each other, and model it as a noncooperative simultaneous game. We choose to model these interactions as a Generalized Nash Equilibrium problem (GNEP)[1]. An alternative could be to consider a leader–follower game in which the automaker is the leader and the ISSP is the follower. The rationale for this alternative would be that, while vehicles can operate without digitalized infrastructure, the reverse is not true. However, because of the premise of our work – namely, that reaching full vehicle-automation might be infeasible or too costly to society – vehicles are dependent on infrastructure digitalization in our setting, leading to a chicken-and-egg problem. Therefore, imposing the precedence structure inherent in a leader–follower game might not be appropriate. Let $\mathbf{v}_i = \{v_{ik}\}$. $\{\mathbf{p}^*, \mathbf{x}^*, \mathbf{z}^*, \boldsymbol{\tau}^*\}$ constitutes a Generalized Nash Equilibrium (GNE) if there exists $\{\mathbf{v}_i^*\}$ such that:

$$\begin{aligned} \{\mathbf{x}^*, \mathbf{p}^*, \{\mathbf{v}_i^*\}\} = \quad & \underset{x_i, p_i, V_k, v_{ik} \ge 0}{\arg\max} \quad \sum_i p_i \cdot x_i \cdot d_i - c_c(x_i, d_i) \\ & \text{s.t.} \quad \{\mathbf{p}, \mathbf{x}, \mathbf{z}^*, \boldsymbol{\tau}^*, \{\mathbf{v}_i\}\} \in X(\mathbf{v}) \end{aligned} \tag{5}$$

and

$$\begin{aligned} \{\mathbf{z}^*, \boldsymbol{\tau}^*, \{\mathbf{v}_i^*\}\} = \quad & \underset{z_k, \tau_k, V_k, v_{ik} \ge 0}{\arg\max} \quad \sum_k [\tau_k \cdot V_k \cdot l_k + \sum_i b_r(x_i, z_k, V_k) \cdot v_{ik} \cdot d_i] - \kappa_r \cdot c_r(z_k, l_k) \\ & \text{s.t.} \quad \{\mathbf{p}^*, \mathbf{x}^*, \mathbf{z}, \boldsymbol{\tau}, \{\mathbf{v}_i\}\} \in X(\mathbf{v}) \end{aligned} \tag{6}$$

where $\mathbf{v} = \{v_i\}$; and $X(\mathbf{v})$ characterizes the set of all $\{\mathbf{p}, \mathbf{x}, \mathbf{z}, \boldsymbol{\tau}, \{\mathbf{v}_i\}\}$ for which $\{\mathbf{x}, \{\mathbf{v}_i\}\}$ is users' response to $\{\mathbf{p}, \mathbf{z}, \boldsymbol{\tau}\}$ due to utility maximization. The utility maximization problem for a user of type i is given by:

$$\begin{aligned} \max_{x_i, v_{ik}} \quad & U_i = \sum_k [f_k(x_i, z_k, V_k, v_{ik}) - \tau_k \cdot v_{ik}] - \kappa_c \cdot p_i \cdot x_i \\ \text{s.t.} \quad & \sum_k v_{ik} = v_i \\ & v_{ik} \ge 0 \quad \forall k \in K \end{aligned} \tag{UM}$$

[1] For distinction between Nash Equilibrium and Generalized Nash Equilibrium problems, please see Facchinei and Kanzow (2010). The basic distinction is that the feasibility set of a given player is affected by the strategies of other players in a Generalized Nash Equilibrium problem but not in a Nash Equilibrium problem.

UM assumes that when a user i routes themselves selfishly in the network, they take the traffic volume V_k as given. This assumption is implicitly made in the literature of traffic network equilibrium analysis (e.g., Sheffi, 1984) and is particularly valid when the number of users is sufficiently large. The first-order necessary conditions (FONC) of UM yield:

$$\sum_k f_{k,1}(x_i, z_k, V_k, v_{ik}) \cdot v_{ik} = \kappa_c \cdot p_i \quad \forall i \in I \quad \text{(Pricing constraint)} \tag{7a}$$

$$v_{ik} \cdot [f_{k,4}(x_i, z_k, V_k, v_{ik}) - \tau_k - \mu_i] = 0 \quad \forall k \in K, \quad \forall i \in I \quad \text{(Complementarity)} \tag{7b}$$

$$f_{k,4}(x_i, z_k, V_k, v_{ik}) - \tau_k - \mu_i \leq 0 \quad \forall k \in K, \quad \forall i \in I \quad \text{(Link travel cost condition)} \tag{7c}$$

$$\sum_k v_{ik} = v_i \quad \forall i \in I \quad \text{(VMT constraint for user } i\text{)} \tag{7d}$$

$$v_{ik} \geq 0 \quad \forall k \in K, \quad \forall i \in I \tag{7e}$$

where Eqs. (7a)–(7d) indicate that the benefit of all road groups used by user i is equal and greater than the benefit of all other unused road groups. μ_i is the Lagrangian multiplier associated with the ith VMT constraint, capturing the net benefit from miles traveled for a user of type i. Then, X is the set of all $\{\mathbf{p}, \mathbf{x}, \mathbf{z}, \boldsymbol{\tau}, \{\mathbf{v}_i\}\}$ such that Eqs. (7a)–(7d) and Eqs. (8a)–(8b) below are satisfied:

$$V_k \cdot l_k = \sum_i v_{ik} \cdot d_i \quad \forall k \in K \quad \text{(Flow conservation constraint for road } k\text{)} \tag{8a}$$

$$\mu_i \cdot v_i \geq \kappa^c \cdot p_i \cdot x_i \quad \forall i \in I \quad \text{(Individual rationality constraint)} \tag{8b}$$

Here, Eq. (8b) indicates that, if there exists an equilibrium, then the user benefit from travel must be enough to justify the purchase of a vehicle. We note that Eq. (7a) to Eq. (8a) make profit maximization for both the automaker and the service provider mathematical programs with equilibrium constraints. To facilitate our analysis, we therefore consider a more restrictive case when all road groups are used by all user groups. Then, for $k \in K$, τ_k is such that:

$$\tau_k = f_{k,4}(x_i, z_k, V_k, v_{ik}) - \mu_i = \frac{1}{V_k \cdot l_k} \cdot \sum_i [f_{k,4}(x_i, z_k, V_k, v_{ik}) - \mu_i] \cdot v_{ik} \cdot d_i \tag{9}$$

The problem for the automaker becomes:

$$\begin{aligned} \max_{\substack{x_i \\ V_k, v_{ik}}} \quad & \sum_i \left[\left(\sum_k f_{k,1}(x_i, z_k, V_k, v_{ik}) \right) \cdot x_i \cdot d_i - \kappa_c \cdot c_c(x_i, d_i) \right] \\ \text{s.t.} \quad & \sum_k f_{k,1}(x_i, z_k, V_k, v_{ik}) = \kappa_c \cdot p_i \quad \forall i \in I, \\ & \tau_k \cdot V_k \cdot l_k = \sum_i (f_{k,4}(x_i, z_k, V_k, v_{ik}) - \mu_i) \cdot v_{ik} \cdot d_i \quad \forall k \in K, \\ & \sum_k v_{ik} = v_i \quad \forall i \in I, \\ & V_k \cdot l_k = \sum_i v_{ik} \cdot d_i \quad \forall k \in K, \\ & \mu_i \cdot v_i \geq \left(\sum_k f_{k,1} \right) \cdot x_i \quad \forall i \in I, \end{aligned} \tag{M}$$

Then, the FONC yield:

$$d_i \cdot \sum_k \left[f_{k,1} \cdot \left(1 + \delta_k^c - \frac{\gamma_i^c}{d_i} \right) + f_{k,11} \cdot \left(1 - \frac{\gamma_i^c}{d_i} \right) \cdot x_i \right] = \kappa_c \cdot c_{c,1}(x_i, d_i) \quad \forall i \in I \tag{10a}$$

$$f_{k,14} \cdot \left(1 - \frac{\gamma_i^c}{d_i} \right) \cdot x_i + (f_{k,44} \cdot v_{ik} + f_{k,4}) \cdot \delta_k^c + \alpha_k^c = \frac{\beta_i^c}{d_i} + \delta_k^c \cdot \mu_i \quad \forall i \in I, \ \forall k \in K \tag{10b}$$

$$\sum_i \left[f_{k,3} \cdot \delta_k^c + f_{k,13} \cdot \left(1 - \frac{\gamma_i^c}{d_i} \right) \cdot x_i \right] \cdot d_i = (\delta_k^c \cdot \tau_k + \alpha_k^c) \cdot l_k \quad \forall k \in K \tag{10c}$$

$$\gamma_i^c \cdot \left[\sum_k f_{k,1} \cdot x_i - \mu_i \cdot v_i \right] = 0 \quad \forall i \in I \tag{10d}$$

$$\gamma_i^c \geq 0 \quad \forall i \in I \tag{10e}$$

where δ_k^c is the Lagrangian multiplier associated with the fee constraint; β_i^c is the Lagrangian multiplier associated with the ith individual VMT constraint; α_k^c is the Lagrangian multiplier associated with the kth traffic volume constraint; γ_i^c is the Lagrangian multiplier associated with the ith individual rationality constraint.

Firstly, we note that, when all road groups are used, $\delta_k^c \geq 0$. Indeed, in the more general case, the manufacturer is faced with $\tau_k \cdot V_k \cdot l_k \geq \sum_i (f_k(x_i, z_k, V_k, v_{ik}) - \mu_i \cdot v_{ik}) \cdot d_i \ \forall k \in K$. This implies that the Lagrangian multiplier δ_k^c would be non-negative for all used road groups. Then, by comparing Eq. (4a) and Eq. (10a), we note that there may be under-provision or over-provision of automation under the GNE. On the one hand, the automaker's exercise of market power (captured by $\sum_k f_{k,11} \cdot x_i < 0$ in Eq. (10a)), induces a lower automation level than what would happen under the social optimum. Moreover, due to the lack of coordination with the service provider, the automaker does not account for the non-pricing benefit (captured by $\sum_k b_{r,1} \cdot v_{ik} > 0$ in Eq. (4a)) when making its production decisions. This, in turns, leads to a lower provision than socially optimal. On the other hand, the ability of the automaker to affect and exploit changing travel patterns for increased gains (captured by $\sum_k f_{k,1} \cdot \delta_k^c > 0$ in Eq. (10a)) could lead to more investment than socially optimal. In an environment with relatively high competition and in which infrastructure-related non-pricing benefits are uncertain or inaccessible for the automaker, the net effect of the automaker's decisions might be too much spending on automation.

The problem for the service provider becomes:

$$\begin{aligned}
\max_{\substack{z_k,\tau_k,\\ V_k,v_{ik}}} \quad & \sum_k \tau_k \cdot V_k \cdot l_k + \sum_i b_r(x_i, z_k, V_k) \cdot v_{ik} \cdot d_i - \kappa_r \cdot c_r(z_k, l_k) \\
\text{s.t.} \quad & \sum_k f_{k,1}(x_i, z_k, V_k, v_{ik}) = \kappa_c \cdot p_i \quad \forall i \in I, \\
& \tau_k \cdot V_k \cdot l_k = \sum_i (f_{k,4}(x_i, z_k, V_k, v_{ik}) - \mu_i \cdot v_{ik}) \cdot d_i \quad \forall k \in K, \\
& \sum_k v_{ik} = v_i \quad \forall i \in I, \\
& V_k \cdot l_k = \sum_i v_{ik} \cdot d_i \quad \forall k \in K, \\
& \mu_i \cdot v_i \geq \left(\sum_k f_{k,1}\right) \cdot x_i \quad \forall i \in I,
\end{aligned} \tag{O}$$

The FONC then yield:

$$\sum_i \left(f_{k,2} + b_{r,2} \cdot v_{ik} - \frac{\lambda_i^r + \gamma_i^r \cdot x_i}{d_i} \cdot f_{k,12} \right) \cdot d_i = \kappa_r \cdot c_{r,1}(z_k, l_k) \quad \forall k \in K \tag{11a}$$

$$-\frac{\lambda_i^r + \gamma_i^r \cdot x_i}{d_i} \cdot f_{k,14} + (f_{k,44} \cdot v_{ik} + f_{k,4}) + b_r + \alpha_k^r = \frac{\beta_i^r}{d_i} + \mu_i \quad \forall k \in K,\ \forall i \in I \tag{11b}$$

$$\sum_i \left[f_{k,34} + b_{r,3} \cdot v_{ik} - \frac{\lambda_i^r + \gamma_i^r \cdot x_i}{d_i} \cdot f_{k,13} \right] \cdot d_i = \alpha_k^r \cdot l_k \quad \forall k \in K \tag{11c}$$

$$\gamma_i^r \cdot \left[\sum_k f_{k,1} \cdot x_i - \mu_i \cdot v_i \right] = 0 \quad \forall i \in I \tag{11d}$$

$$\gamma_i^r \geq 0 \quad \forall i \in I \tag{11e}$$

where λ_i^r is the Lagrangian multiplier associated with the ith pricing constraint; β_i^r is the Lagrangian multiplier associated with the ith flow balance constraint; γ_i^r is the Lagrangian multiplier associated with the ith individual rationality constraint; and α_k^r is the Lagrangian multiplier associated with the kth traffic volume constraint. Here too, with arguments similar to those for the positivity of δ_k^c in the automaker's case, it is possible to deduce that $\lambda_i^r \geq 0$ at equilibrium.

Now, considering Eq. (11a), if automation and digitalization are substitutes ($f_{k,12} \leq 0$), then there is over-provision of digitalization relative to the social optimum (with equal provision when $f_{k,12} = 0$). Simply, in order to have a competitive edge and capture users' willingness to pay, the service provider invests heavily in digitalization. If automation and digitalization are complementary ($f_{k,12} > 0$), there is under-provision of digitalization at the Nash equilibrium. Because of a coordination failure, the service provider is reluctant to invest in digitalization: she cannot ensure that the automaker will make the compatible automation investment that will make the digitalization investment worthwhile.

3.3. Cooperation

Our analysis above shows that, in the absence of coordination, it is likely that the level of automation and digitalization are suboptimal. This sub-optimality is due, on one hand, to a lack of coordination between service providers and car manufacturers and, on the other, to the car manufacturer's exercise of market power (as attested by the presence of a markup in Eq. (10a)). We discuss here how the former issue could be resolved. In order to achieve coordination, a contract that ensures that both the operator and the manufacturer are better off working together can be designed. Such a contract must meet the following criteria:

- The joint profit π^T must be maximized: $\pi^T = \pi^c + \pi^r$
- Each party must be better off than under the GNE: $\pi^{c,GNE} \leq \pi^{c,CE}$ and $\pi^{r,GNE} \leq \pi^{r,CE}$

where $\pi^{a,GNE}$ refers to the profit under the GNE and $\pi^{a,CE}$ refers to the profit under the cooperative equilibrium (CE) with $a \in \{c, r\}$. Following the Nash bargaining, $\pi^{c,CE}$ and $\pi^{r,CE}$ are such that:

$$\begin{aligned}
(\pi^{c,CE}, \pi^{r,CE}) = \quad & \underset{\substack{\pi^c \geq \pi^{c,GNE},\\ \pi^r \geq \pi^{r,GNE}}}{\text{argmax}} \quad (\pi^c - \pi^{c,GNE}) \cdot (\pi^r - \pi^{r,GNE}) \\
& \text{s.t.} \quad \pi^c + \pi^r = \pi^{T,CE}
\end{aligned} \tag{NB}$$

where:

$$\begin{aligned}\pi^{T,CE} = \max_{\substack{x_i,p_i,v_{ik},\\ z_k,\tau_k,V_k\geq 0}} \quad & \kappa_c \cdot \sum_i \Big[p_i \cdot x_i \cdot d_i - c_c(x_i,d_i) - m_c(\bar{x})\Big] + \sum_k \tau_k \cdot V_k \cdot l_k - \kappa_r \cdot c_r(z_k,l_k) \\ & + \sum_k \sum_i b_r(x_i,z_k,V_k,v_{ik}) \cdot v_{ik} \cdot d_i \\ \text{s.t.} \quad & \{\mathbf{p},\mathbf{x},\mathbf{z},\boldsymbol{\tau},\{\mathbf{v}_i\}\} \in X(\mathbf{v})\end{aligned} \tag{TM}$$

It is easy to show that:

$$\pi^{c,CE} = \pi^{c,GNE} + \phi \cdot \Big[\pi^{T,CE} - \pi^{c,GNE} - \pi^{r,GNE}\Big] \tag{12}$$

$$\pi^{r,CE} = \pi^{r,GNE} + (1-\phi) \cdot \Big[\pi^{T,CE} - \pi^{c,GNE} - \pi^{r,GNE}\Big] \tag{13}$$

where $\phi \in (0,1)$ represents the share of excess profits – relative to the GNE – that the automaker will pocket. Now, the question arises as to whether cooperation is welfare-improving relative to the GNE. Assuming, as in M and O, that all road groups are utilized by all user groups, then TM becomes:

$$\begin{aligned}\pi^{T,CE} = \max_{\substack{x_i,\bar{x},v_{ik},\\ z_k,V_k,v_{ik}\geq 0}} \quad & \sum_i \Big(\sum_k f_{k,1}(x_i,z_k,V_k,v_{ik}) \cdot x_i + b_r(x_i,z_k,V_k) \cdot v_{ik}\Big) \cdot d_i - \kappa_c \cdot \sum_i c_c(x_i,d_i) \\ & + \sum_k \sum_i (f_{k,4}(x_i,z_k,V_k,v_{ik}) - \mu_i) \cdot v_{ik} \cdot d_i - \sum_k \kappa_r \cdot c_r(z_k,l_k) \\ \text{s.t.} \quad & \sum_k v_{ik} = v_i \quad \forall i \in I, \\ & V_k \cdot l_k = \sum_i v_{ik} \cdot d_i \quad \forall k \in K, \\ & \mu_i \cdot v_i \geq \sum_k f_{k,1}(x_i,z_k,V_k,v_{ik}) \cdot x_i \quad \forall i \in I,\end{aligned} \tag{TM}$$

and the FONC yields:

$$d_i \cdot \sum_k \Big[f_{k,1} + b_{r,1} \cdot v_{ik}\Big] = \kappa_c \cdot c_{c,1}(x_i,d_i) \quad \forall i \in I \tag{14a}$$

$$\sum_i \Big[f_{k,2} + b_{r,2} \cdot v_{ik}\Big] \cdot d_i = \kappa_r \cdot c_{r,1}(z_k,l_k) \quad \forall k \in K \tag{14b}$$

$$\sum_i \Big[f_{k,3} + b_{r,3} \cdot v_{ik}\Big] \cdot d_i = \alpha_k \cdot l_k \quad \forall k \in K \tag{14c}$$

$$f_{k,4} + b_r + \alpha_k = \frac{\beta_i}{d_i} + \mu_i \quad \forall k \in K, \forall i \in I \tag{14d}$$

Comparing Eq. (14) to Eqs. (10) and (11) indicates that, relative to the Nash equilibrium, cooperation:

- reduces the effect of the manufacturer's market power and increases the provision of automation;
- increases (decreases) provision of digitalization when digitalization and automation are complements (substitutes)

Thus, cooperation between the car manufacturer and the service provider increases surplus. Additionally, comparing Eqs. (4) and (14), cooperation between the manufacturer and the operator will decentralize the social optimum if:

$$\frac{\gamma_i}{d_i} = \frac{\beta_i}{d_i} + \mu_i \tag{15}$$

In other words, if the marginal benefit of travel $\frac{\beta_i}{d_i} + \mu_i$ for the combined entity is equal to the marginal benefit of travel for the social planner, cooperation will achieve the first-best. Otherwise, cooperation achieves the second-best: $\frac{\beta_i}{d_i} + \mu_i < \frac{\gamma_i}{d_i}$. This can potentially be the best-case scenario absent the possibility of subsidies (e.g., when the first-best is not sustainable for either or both companies).

4. A numerical example

We propose here to illustrate our model's results as well as other properties.

4.1. Functions and parameters

We consider $K = 3$ road groups and $I = 3$ different user groups. The road lengths l_k and capacities V_k^{max}, users' daily VMT v_i and population d_i as well as other parameter values and how they were obtained can be found in Appendix. It suffices to say, however, that K and I are ordered in an increasing order of capacity and daily VMT respectively.

Automation and digitalization levels vary continuously from 1 to 100. We assume the following cost and benefit functions:

$$f_k(x_i,z_k,V_k,v_{ik}) = \left[f_{0t} \cdot \left[\alpha \cdot (x_i)^\rho + (1-\alpha) \cdot (z_k)^\rho\right]^{\frac{v}{\rho}} - f_{0c} \cdot \left(\frac{V_k}{V_k^{max}}\right)^2\right] \cdot \sqrt{v_{ik}} \tag{16a}$$

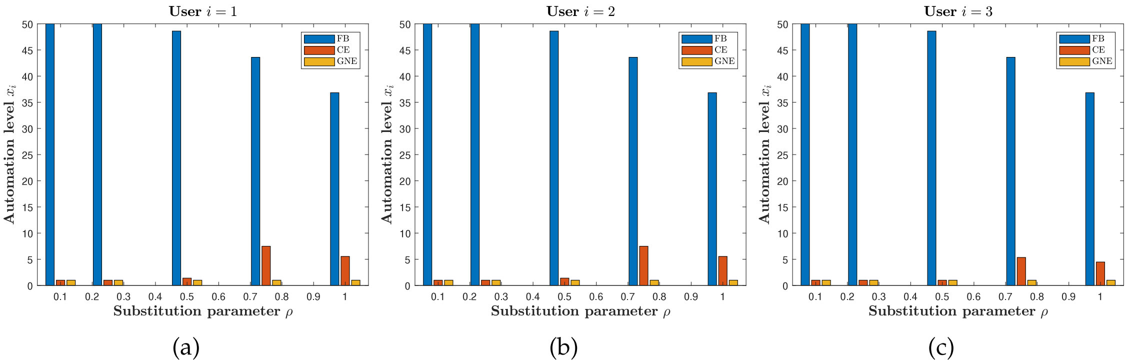


Fig. 1. Effect of substitution parameter on automation level.

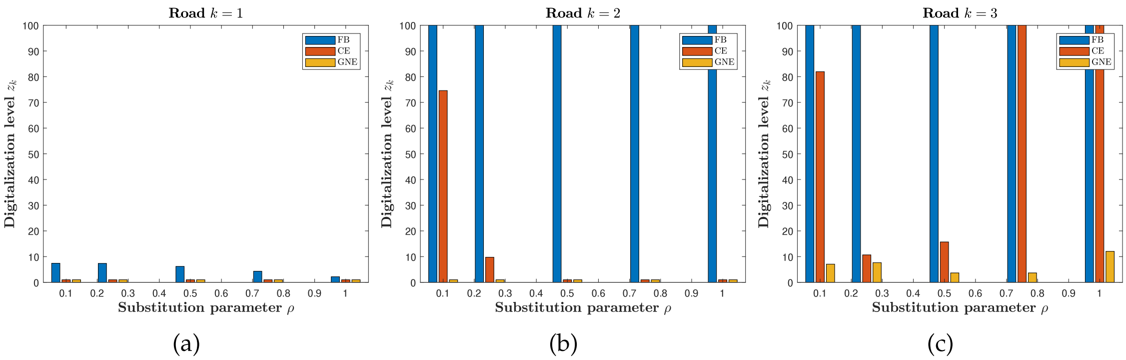


Fig. 2. Effect of substitution parameter on digitalization level.

$$\sum_i c_c(x_i, d_i) = m_{c,0} \cdot \max_j x_j + \sum_i [c_0 + c_1 \cdot (x_i)^2] \cdot d_i \tag{16b}$$

$$b_r(x_i, z_k, V_k) = b_0 \cdot (x_i)^\gamma \cdot (z_k)^\theta \cdot \left(\frac{V_k}{V_k^{max}}\right)^{\eta_r} \tag{16c}$$

$$c_r(z_k, l_k) = m_{r,0} \cdot l_k \cdot (z_k)^2 \tag{16d}$$

Eq. (16a) indicates that automation and digitalization interact following a constant elasticity of substitution (CES) utility function. Thus, ρ is the substitution parameter: as ρ increases, automation and digitalization become more substitutable in the eyes of customers. Additionally, drivers' benefit from automation and digitalization will be affected by a congestion cost.

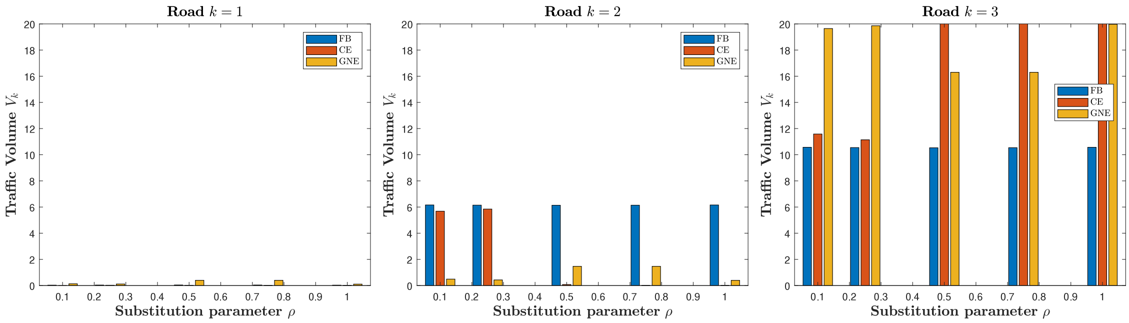
Eq. (16b) indicates that the total cost of manufacturing includes both an investment cost $m_{c,0} \cdot \max_j x_j$ – the cost the company must pay to develop its highest level of automation – and production costs $[c_0 + c_1 \cdot (x_i)^2] \cdot d_i$ for each automation levels.

The parameters of the model as well as their value are given in Appendix.

4.2. Effect of substitution parameter

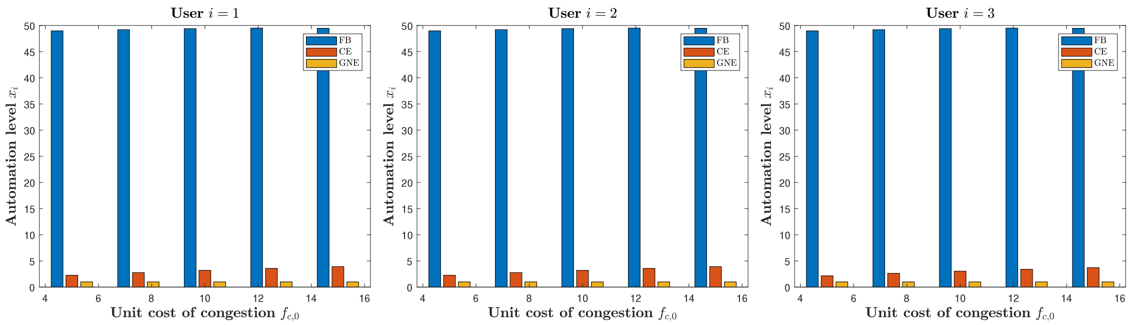
Figs. 1 and 2 show the level of automation and digitalization, respectively, as a function of the degree of substitution under the three different scenarios considered in this study: the social optimum (FB), the cooperative equilibrium (CE) and the GNE. First, we note that as automation and digitalization levels become more substitutable, the socially optimal automation level decreases. Simply, because customers are increasingly indifferent between automation and digitalization and because digitalization can serve multiple classes simultaneously, the need for automation diminishes. Moreover, the road groups with the highest volumes receive the highest levels of digitalization (Figs. 2 and 3). As expected, the CE improves welfare relative to the GNE, though it still falls short from the socially optimal configuration[2]. The improvement of CE over the GNE is more pronounced as substitutability increases, thus highlighting the crippling effect of competition.

[2] The elasticity of demand will determine the size of the gap between CE and GNE. In our case, because demand is inelastic, the gap will be larger.



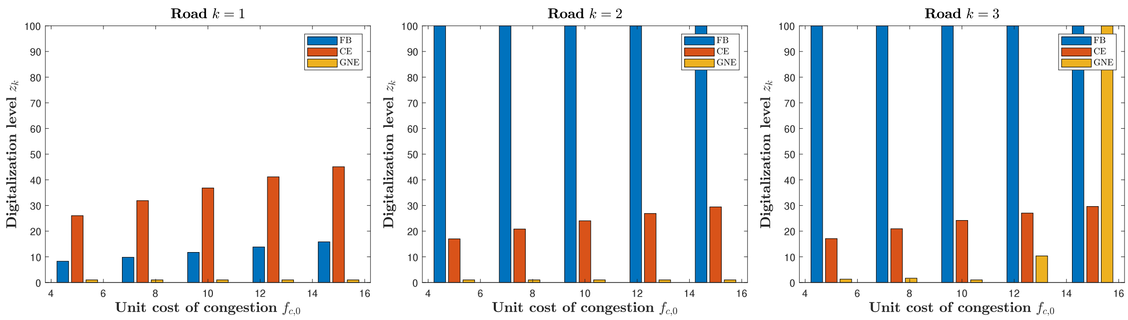
(a) (b) (c)

Fig. 3. Effect of substitution parameter on traffic volume distribution.



(a) (b) (c)

Fig. 4. Effect of congestion cost on automation level.

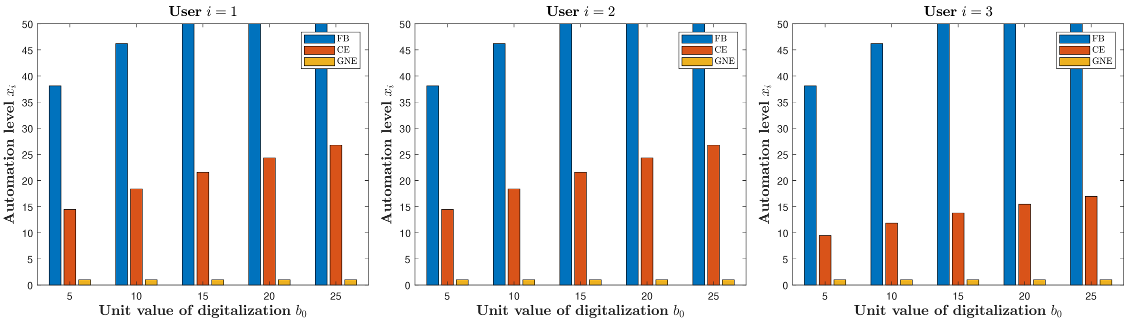


(a) (b) (c)

Fig. 5. Effect of congestion cost on digitalization level.

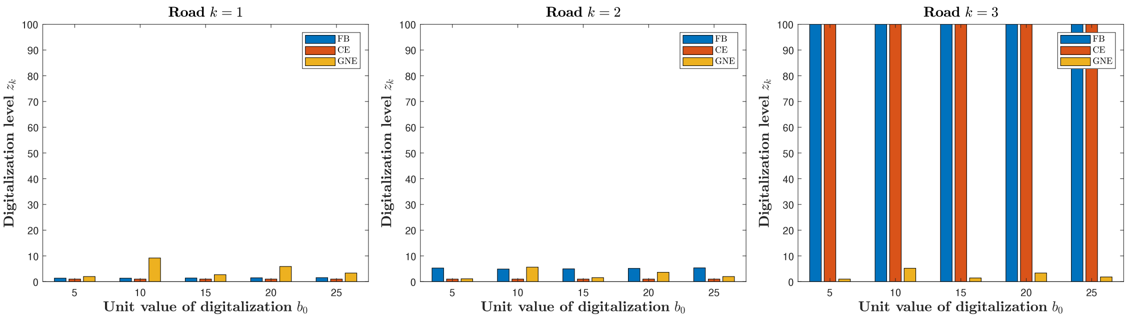
4.3. Effect of unit cost of congestion

Here, we evaluate the impact of the cost of congestion, $f_{c,0}$, on equilibrium results. In practice, this can shed light on the difference in automation choices between users with different values of time. As Figs. 4 and 5 show, some of main insights from Section 4.2 still hold. Namely, cooperation usually results in better performance than competition but performs worse than the surplus maximizing configuration. As we would expect, increasing congestion costs leads to an increase in both automation and digitalization investment, though the effect is more pronounced on the infrastructure side. Simply, the higher the cost of congestion, the higher the value of automation and digitalization. Thus, investing in automation and digitalization in highly congested areas would seem like an intuitive first step for both the private and public sector.



(a) (b) (c)

Fig. 6. Effect of the value of digitalization on automation level.



(a) (b) (c)

Fig. 7. Effect of the value of digitalization on digitalization level.

4.4. Effect of unit monetary value of digitalization

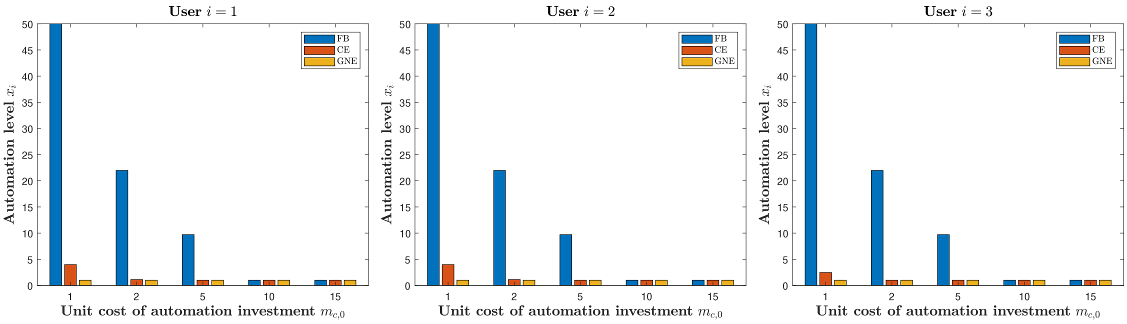
There is uncertainty as to what the monetary benefits of digitalization, b_0, will be for ISSPs. Such benefits will depend, among other things, on the existence of a vibrant market for road data that only infrastructure digitalization could fulfill. To better understand the effect of that monetary value, we vary b_0 across the three scenarios considered. The results are shown in Figs. 6 and 7. It is interesting to note that, in the FB and CE cases, an increase in the value of digitalization leads to an increase in equilibrium automation levels. In essence, because digitalization and automation interact together to generate value, there is an incentive for the social planner and for any joint venture between automaker and ISSP to increase automation levels.

4.5. Effect of automation development costs

Lastly, because one of the main motivations for the present work is the high cost of automation, we propose to investigate the effect of development costs, $m_{c,0}$, on the outcome of our scenarios. The results are shown in Figs. 8 and 9. First, we note that, because of the co-dependency between automation and digitalization in generating value, increasing automation costs lead to a reduction in both automation and digitalization for both the social planner and the integrated company. Essentially, the more expensive automation becomes, the lesser the value to both society and the private sector of implementing our vision for vehicle-infrastructure cooperation. Thus, a careful evaluation of the costs and benefits of automation is needed. In the GNE case, the ISSP obviously benefits from the higher automation costs and increases its provision of digitalization beyond the efficient levels to increase profits.

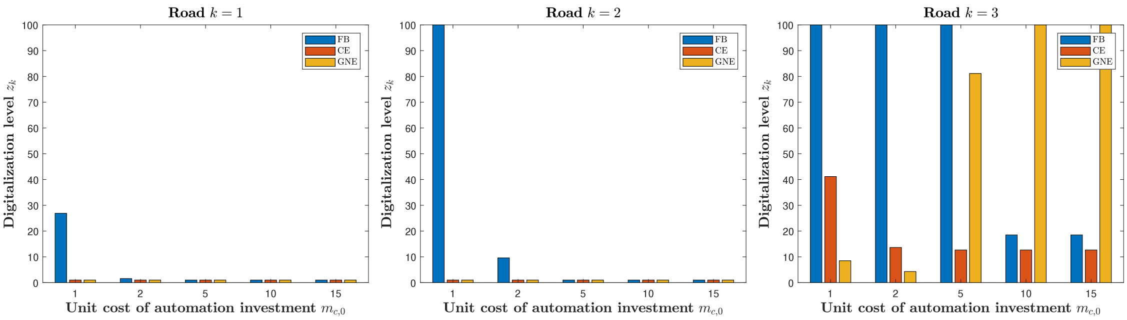
5. Conclusion

This paper has investigated vehicle-infrastructure cooperation for enabling automated driving. In this cooperation, the infrastructure can perform driving tasks such as sensing, perception or planning, and essentially becomes an integral part of the driving system of an automated vehicle. By proposing and analyzing a model that captures investment decisions in automation and digitalization and their effect on travelers' purchase and travel decisions, we have shown that such a vehicle-infrastructure cooperative paradigm can be socially optimal. Subsequently, we also show that strategic interactions between a monopolistic automaker and a monopolistic service provider result in suboptimal investment in both automation and digitalization. The suboptimality of automation is due, in part, to the lack of coordination which prevents automakers from enjoying the non-pricing benefits that driving generates for



(a) (b) (c)

Fig. 8. Effect of automation development cost on automation level.



(a) (b) (c)

Fig. 9. Effect of automation development cost on digitalization level.

service providers. Whether there is over-investment or under-investment in automation will also depend on the travel behaviors of the different user groups. Users with high VMT will likely see higher than optimal automation while those with low VMT will receive lower than optimal automation. For service providers, when automation and digitalization are substitutes, there is over-investment in digitalization technology as service providers seek to compete with the automation technology. However, when they are complements, service providers are reluctant to invest in digitalization: there is no enforcement mechanism that guarantees that automakers will invest in compatible automation levels. It is then easy to show that, given an appropriate profit-sharing agreement between the two actors, cooperation could yield the socially optimal levels of automation and digitalization. Thus, from a planning perspective, better coordination of infrastructure standards and regulation across states should be a priority. Such coordination across service providers will then provide automakers with the opportunities for economies of scale that would be otherwise lacking when developing the infrastructure-assisted vehicle technology. Finally, it will provide service providers and/or their regulating entities with the value proposition necessary to benefit from vehicle-infrastructure cooperation.

In this work, we assume that users' demand for travel and automation is fixed. However, since automation and digitalization reduce the cost of travel, an increase in VMT is likely after adoption of these technologies and can have two conflicting effects which it will be necessary to investigate. On one hand, by increasing VMT, it could increase the ISSP's ability to generate profits. On the other, that increase in VMT can increase congestion and reduce willingness to pay for road usage. Moreover, such an increase in VMT can also have a negative social impact. Thus, future iterations will consider the case of elastic travel demands. Moreover, by enabling mobility-as-a-service, automation will also provide an alternative to car ownership for users. As such, automakers face an additional dilemma in providing automation, but also another earning opportunity. The impact of these decisions and their effects on VMT will also be incorporated. Lastly, we have not accounted here for competition among automakers and among service providers. Essentially, there is no product differentiation in either the vehicle or infrastructure market. This makes it difficult to assess the benefits–or lack thereof–that can accrue to different socio-demographic groups. Our model can be extended and made more realistic to include the effects on investment of these new strategic interactions and the relevant incentives to be provided. Also, the question of investment is essentially a dynamic problem subject to uncertainty and the different agents involved will make repeated decisions that can significantly alter the trajectory of both automation and digitalization levels. Such rich dynamics is not captured by the current model and will need to be incorporated. Lastly, we have not analyzed equilibrium properties for our GNEP. This could provide additional insights as to competition/cooperation between automakers and ISSPs and will be explored in future work.

Table 2
Parameter values for numerical examples.

i	Population size (millions)	Daily VMT v_i (miles)
1	60.75	75
2	61.80	45
3	167.15	15

Table 3
Parameter values for numerical examples.

k	Road type	Length (ten thousands)	Capacity V_k^{max} (thousands)
1	Local	290.69	4.79
2	Collector	79.2	5.01
3	Arterial	46.15	7.07

CRediT authorship contribution statement

Daniel A. Vignon: Methodology, Investigation, Writing – original draft. **Yafeng Yin:** Conceptualization, Methodology, Writing – review & editing, Supervision, Funding acquisition. **Sina Bahrami:** Methodology, Investigation. **Ken Laberteaux:** Conceptualization, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix. Parameter values

A.1. User groups

We identify user groups and their population distribution using data from the 2017 National Household Travel Survey (NHTS) (McGuckin and Fucci, 2018). We also use the total VMT implied by the data to compute a VMT distribution suitable for our numerical examples. The resulting parameters can be seen in Table 2.

A.2. Road groups

We identify road types in our example using classification from the Federal Highway Administration (FHWA) (NYDOT, 2021). We then identify the relevant parameters in Table 3 using FHWA 2018 statistics for VMT, total miles built, number of lane-miles for each category. Capacity for each road type is determined using guidelines from (Margiotta and Washburn, 2017).

A.3. Other parameters

The other parameters used in our numerical example are listed in Table 4. f_0 and b_0 are approximated by using estimates of the total savings at full automation in Clements and Kockelman (2017) and the total yearly VMT in the US. The base manufacturing cost is obtained by using the average selling price of a car in 2016 (Statista, 2019) and assuming $\$1,500$ in profits for the car manufacturer. κ_c and κ_r are calculated by assuming a discount factor of 5% and assuming that users will own their car for 7 years while operators will operate the roads for 25 years. $m_{c,0}$ and $m_{r,0}$ will likely be higher in practice, but these are values that make our numerical experiments easier.

Table 4
Parameter values for numerical examples.

Notation	Interpretation	Value
f_0	User monetary value of a mile driven	¢5
b_0	Operator monetary value of a mile driven	¢15
$f_{c,0}$	Cost of congestion per mile driven	¢20
c_0	Base vehicle manufacturing cost	$\$30,000$
c_1	Manufacturing cost per unit of automation	$\$2,500$
$m_{c,0}$	Vehicle investment cost per unit of automation	$\$155,000$
$m_{r,0}$	Road unit investment per unit of digitalization	$\$5,000$
α	Utility automation share	0.6
ρ	Substitution parameter	0.5
υ	Degree of homogeneity	2
η_c	Customer congestion elasticity	0.2
η_r	Operator congestion elasticity	0.4
γ	Operator automation elasticity	0.2
θ	Operator digitalization elasticity	0.4
κ_c	Amortization parameter for vehicle purchase	0.15
κ_r	Amortization parameter for road investment	0.07

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