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Automated vehicle diffusion under uncertainty across national and regional scenarios in Brazil

Difusão de veículos autônomos sob incerteza em cenários nacionais e regionais no Brasil

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ABSTRACT
The global transition toward mobility based on automated and autonomous vehicles (AVs) poses a challenge for transportation planning, requiring the analysis of scenarios where these vehicles will be introduced and disseminated throughout the fleet. International studies suggest prolonged transition periods and uncertainty regarding the widespread adoption of AVs due to barriers such as additional costs, safety concerns, and coexistence with conventional vehicles. In Brazil, however, scenarios concerning the introduction and dissemination of AVs in the vehicle fleet remain underexplored. This paper presents a scenario analysis of the introduction and dissemination of AVs in the Brazilian passenger car fleet over the coming decades. A model is proposed based on estimated new-vehicle sales and registrations, and the availability of automation technologies in the domestic market. Results show that the share of AVs in the Brazilian fleet is expected to increase gradually over the long term. Under optimistic scenarios, simulations indicate that fully autonomous vehicles are unlikely to account for more than 50% of the Brazilian fleet by 2060, suggesting the coexistence of vehicles with different levels of automation. These findings highlight the need for long-term strategic planning to support vehicle transition, including the regulatory and infrastructure challenges inherent in a mixed-fleet environment.

RESUMO
A transição global para a mobilidade com veículos automatizados e autônomos (VAs) representa um desafio para o planejamento de transportes, exigindo a análise de cenários de introdução e disseminação na frota. Pesquisas internacionais indicam longos períodos de transição e incertezas quanto à adoção plena de VAs, devido a barreiras como custos adicionais, questões de segurança e coexistência com veículos tradicionais. No Brasil, a projeção e os cenários de introdução e disseminação de VAs na frota circulante são temas incipientes. Este artigo apresenta uma análise de cenários de introdução e disseminação de VAs na frota brasileira de automóveis ao longo das próximas décadas. Propõe-se um modelo baseado na projeção de vendas de novos veículos e a disponibilidade de tecnologias de automação no mercado nacional. Os resultados indicam que a participação de VAs na frota brasileira será gradual e de longo prazo. Nos cenários mais favoráveis, as simulações indicam que veículos totalmente autônomos não devem ultrapassar 50% da frota circulante do Brasil até 2060, prevendo a coexistência de diferentes níveis de automação. Essas projeções reforçam a necessidade de planejamento estratégico de longo prazo para a transição veicular no país, com desafios regulatórios e de infraestrutura inerentes a um cenário de frota mista.

1. Introduction

Although the scientific literature on automated and autonomous vehicles (AVs) has expanded substantially in recent years, it often lacks strict distinctions among the different levels of automation established by technical standards. Much of the recent literature employs simulation models to assess interactions between vehicles with and without automation in controlled environments, such as highways, as well as in urban settings and platooning. However, few studies have examined the transition period required for the diffusion of vehicles with varying degrees of automation within the circulating fleet.

Drawing on the National Highway Traffic Safety Administration (NHTSA), Kockelman *et al.* (2017) define automated vehicles as those in which at least some aspects of a safety-critical control function (e.g. steering, acceleration, or braking) occur without direct driver input. In this paper, the definition of AVs encompasses both in-vehicle technologies for driver warnings or assistance, and fully autonomous driving without human intervention.

During the 2010s, studies anticipated the accelerated introduction of AV technologies, even suggesting that fully autonomous vehicles could become widely deployed by the 2030s, as discussed by Hermann, Brenner & Stadler (2018) and Trommer *et al.* (2016). More recent research suggests longer transition periods for these advanced technologies, as noted by Norton (2021) and Xie & Liu (2022).

As of 2023, market trends and academic discourse suggest that, in the short term, the automotive market would be dominated by "robotaxis", with manufacturers supplying chassis to ride-hailing companies (The Economist, 2023), while also acknowledging that full autonomy remains far from widespread adoption. As stated by Norton (2021), the industry's unmet promise of a car-dependent city that is safe, clean, and free of congestion has now evolved into the prospect of a "high-tech car-dependent" city.

The introduction and diffusion of AVs are also uncertain. For instance, Simoni *et al.* (2019) note that it remains unclear whether the market will be led primarily by shared mobility services or by privately owned vehicles. Lipson & Kurman (2017) and Litman (2021) further emphasize that automation adoption is likely to vary according to income disparities across countries. Recent literature, particularly from 2020 onwards, has advanced the understanding of the factors driving AV acceptance and willingness to pay, providing a more refined investigation of psychodemographic and contextual variables. This evidence is essential for modeling more realistic adoption scenarios across diverse global markets.

Regional heterogeneity is especially relevant in developing countries such as Brazil, where socioeconomic conditions, infrastructure patterns, and levels of technological acceptance may lead to distinct adoption dynamics that remain insufficiently addressed in the international literature. Given this scenario of uncertainty and the lack of studies specifically addressing the regional context, this paper presents a framework to assess the introduction and diffusion of AVs within the Brazilian automobile fleet. We modeled fleet evolution over the coming decades to provide preliminary evidence for transport planning in the context of a developing country under conditions of high technological, regulatory, and market uncertainty.

Following this introduction, the paper presents a literature review on automation levels, prospects for AV introduction, and their potential implications for public policy. It is followed by a description of the proposed modeling approach and simulated scenarios, which account for assumptions regarding different levels of automation and regional heterogeneity within the country. Next, the results of the modeling framework applied to the Brazilian context are presented and discussed, followed by conclusions and recommendations for future research.

2. Literature review

2.1. Automation levels

The literature proposes conceptual distinctions between automated and autonomous vehicles, as discussed by Hermann, Brenner & Stadler (2018). According to Bohm & Häger (2015, p. 3):

> [...] autonomous driving generally refers to vehicles with the ability to control the driving without human interaction. This enables humans to delegate driving tasks or the complete driving to the car's control systems but can also include the vehicle taking over the control in situations where the driver cannot cope.

Hence, autonomy refers only to the most advanced stage of driving and navigation technologies, in which human intervention is no longer required. Automation, in turn, encompasses multiple levels of

Table 1 • Levels of automation according to the SAE (2018) classification, adapted from Kappler (2020) and Bentley (2019)

Definition		Features
Level 0	No automation	The driver performs all driving tasks, without any assistance or automated features.
Level 1	Driver assistance	The vehicle is operated by the driver but may include some assistance features operating independently. For example, a lane-keeping feature operates without being associated with emergency braking.
Level 2	Partial automation	The vehicle combines automated functions, such as acceleration, deceleration, and steering tasks; however, the driver must remain in control of all driving tasks and monitor the traffic environment throughout the entire driving period.
Level 3	Conditional automation	The vehicle can operate autonomously, but the driver must be prepared to take control throughout the trip when prompted by the system. Autonomous driving under congested traffic conditions is an example of this level.
Level 4	High automation	The vehicle is capable of performing all driving functions under certain weather and traffic conditions, but the driver may take control of the vehicle. Full automation occurs only in controlled areas, such as segregated lanes.
Level 5	Full automation	The vehicle can perform all driving tasks under all road and weather conditions, without requiring a human driver. The driver may have the option to control the vehicle, if desired.

driving support, including driver-assistance functions and warning systems. Payre, Cestac & Delhomme (2014) argue that full automation must involve longitudinal, lateral, and maneuvering control.

Kockelman & Boyles (2018) and Bansal & Kockelman (2017) suggest that technologies associated with isolated functions, such as warning or assistance systems, may reach maturity in the short term. However, the integration of such functions through a central processing unit, as well as the execution of driving tasks in shared environments, will require longer maturation periods. AV-related functionalities are commonly classified according to levels of automation, among which the Society of Automotive Engineers classification (SAE J3016) summarized in Table 1 is one of the most widely adopted.

Some studies have proposed alternative classification schemes. Atkins (2016) summarizes the SAE J3016 levels into four categories: (a) no automation; (b) driver assistance; (c) partial to high automation; and (d) full automation. Kyriakidis, Happee & de Winter (2015) propose a similar classification: (a) manual driving; (b) partially automated driving; (c) highly automated driving; and (d) fully automated driving. More recently, Deichmann, Grosse-Ophoff & Kässer (2023) proposed a classification into: (a) driver assistance; (b) partial automation; (c) conditional automation; and (d) high automation. The NHTSA classification is similar to SAE J3016 but consists of five categories rather than six (Kockelman *et al.*, 2017).

The distinction among levels of automation does not always clearly specify the technologies or functionalities that characterize each level, making it difficult to differentiate, for example, between SAE J3016 Levels 1 and 2. Kockelman & Boyles (2018) acknowledge that manufacturers offer these systems in varying technology packages, which limits the classification. This feature further constrains the simulation of mixed traffic flow effects, as it is not clear which functionalities are associated with each level. The approach adopted by Xie & Liu (2022) provides a more useful framework for analysis: (1) manual driving, (2) partial automation, and (3) full automation. Figure 1 summarizes the several automation frameworks discussed.

Two types of boundaries between levels of automation may be considered: whether technologies are integrated, and whether functions are limited to driver alerts/support or extend to driving control. One important distinction concerns the combined operation of technologies: lower levels of automation rely on technologies that operate separately to perform specific functions, whereas more advanced levels combine technologies and data within a single processing unit (Schoettle & Sivak, 2014). Vehicles may be equipped with lane-departure warning and parking-assistance devices without these technologies being integrated into a single processing unit. Fully autonomous driving, by contrast, should allow

Table 2 foi transformada em Figure 1

Source	Autonomous Driving Automation Levels					
SAE (2018)	No automation (Level 0)	Driver assistance (Level 1)	Partial automation (Level 2)	Conditional automation (Level 3)	High automation (Level 4)	Full automation (Level 5)
NHTSA (2013)	No automation (Level 0)	Function-specific automation (Level 1)	Combined-function automation (Level 2)	Limited self-driving automation (Level 3)	Full self-driving automation (Level 4)	
BASt (Kyriakidis, Happee & de Winter, 2015)	Drivers only	Assisted driving	Partially autonomous	Highly automated	Fully automated	
NHTSA, synthesis from Kockelman *et al.* (2017)	Drivers only	Drivers assisted by technologies	Drivers share control	Drivers relinquish control under certain conditions	The system assumes all functions	
Schoettle & Sivak (2014) (adapted from NHTSA)	No automation technologies	Vehicles control one or more functions, with independent operation	Vehicles control two or more functions, with combined operation	Limited autonomous driving technologies	Fully autonomous	
Atkins (2016)	No automation	Driving assistance	Partial to high automation		Full automation	
Kyriakidis, Happee & de Winter (2015)	Manual driving	Partially automated driving		Highly automated driving	Fully automated driving	
Xie & Liu (2022); Daziano, Sarrias & Leard (2017)	Manual driving	Partial automation		Full automation		

Figure 1 • Synthesis of the literature review on automation level classification, adapted from Kyriakidis, Happee & de Winter (2015)

different functionalities to converge within the same processing unit.

The other important boundary concerns functionality. Lower levels include devices for alerts, warnings, or assistance, whereas more advanced levels incorporate technologies that operate directly on vehicle control or navigation. Platooning, for example, requires multiple technologies operating jointly and is therefore classified at more advanced levels of automation.

2.2. Prospects for the introduction of AVs

The analysis on the prospective introduction and diffusion of automated vehicles was grouped into three sources of evidence: broad-scope, simulation-based, and user-based. This classification is consistent with Harb *et al.* (2021), who identify three research methods for assessing trust in and acceptance of AV technologies: (a) demand- and agent-based models; (b) interviews; and (c) field experiments.

2.2.1. Broad-scope evidence

These sources of evidence often refer to estimates of AV adoption in either vehicle fleets or sales. Among the more optimistic projections, Lipson & Kurman (2017) predict that, by 2035, autonomous and connected vehicles will account for approximately 10% of the fleet. Hermann, Brenner & Stadler (2018) estimate that fully autonomous vehicles will have a significant market presence by 2030. Trommer *et al.* (2016) project the introduction of Level 5 vehicles (SAE J3016) in Germany by 2030 and one decade earlier in China for luxury cars. The MCFM (2019) suggests that, by 2040, 55% of mobility-service fleets will be autonomous, compared with 11% of privately owned vehicles.

Litman (2021, 2022) argue that these impacts are difficult to predict and that wide adoption rates of automotive innovations require longer time horizons. Litman (2021) estimates that AVs of all categories will remain under testing and development during the 2020s. In the following decade, sales are expected to be limited to high-value luxury vehicles. In the 2040s and 2050s, AVs are projected to become available in mid- and low-cost market segments. These estimates likely apply primarily to developed countries, particularly Canada and the United States. Such scenario leads to a substantial AV presence of approximately 50% of the fleet not expected before 2060. Litman (2022) also notes that autonomous driving technologies rely on adequate pavement conditions, traffic signs and markings, and weather conditions.

Webb (2019) highlights sociodemographic changes that point to reduced dependence on motorized mobility, increased shared mobility, denser urban centers, and youth unemployment, alongside rising costs associated with new technologies. Taken together, these factors suggest constrained new-car sales rather than growth.

Bentley (2019) argues that fully autonomous vehicles remain decades away from large scale sales, whereas operation in controlled environments, such as controlled-access highways, are more feasible. Deichmann, Grosse-Ophoff & Kässer (2023) evaluate the delayed, baseline, and accelerated scenarios and estimate that advanced levels of automation will account for only 17%, 37%, and 57% of new vehicles in 2035, respectively.

2.2.2. Simulation-based evidence

Fulton, Mason & Meroux (2017) propose a mobility model to assess scenarios combining electrification, automation, and shared mobility. They estimate a 10–15-year transition period for AVs in developed countries, occurring sometime between the 2020s and the 2050s. A scenario assuming automation and electrification without substantial shared mobility suggests that AVs will not achieve significant fleet share before 2040.

Bierstedt, Gooze & Grey (2014) proposed progressive scenarios for the introduction of AVs based on different operating environments: between 2025 and 2030, they are expected to operate in dedicated lanes; between 2030 and 2035, in mixed highway lanes; and between 2035 and 2040, on arterial roads. Such vehicles are expected to operate on public roads only by 2050.

Xie & Liu (2022) investigated the effects of connected and autonomous vehicles (CAVs) on market share and route choice in mixed traffic networks. They develop a market equilibrium model that considers the interaction between vehicle markets and road traffic through market penetration, information quality, and congestion distribution. Xie and Liu (2022) conclude that the initial adoption of AVs will be limited because of high acquisition costs, but that adoption will increase with technological advances and mass production. Fully automated vehicles are expected to dominate the market, whereas partially automated vehicles are likely to be progressively phased out.

Santana, Silva & Figueiredo (2021) developed a mesoscopic simulation model that considers a system in which autonomous vehicles coexist with human-driven vehicles on an arterial road network in São Paulo, Brazil, comprising exclusive AV lanes, platooning, synchronized traffic signals, smaller vehicles, and the current configuration. They suggest that the expected benefits may not be achieved under all the scenarios examined and that AV diffusion is likely to face substantial challenges in real-world urban settings.

2.2.3. User-based evidence

Recent research has examined how psychodemographic factors, including income, perceived safety, prior experience with automated technologies, and other demographic characteristics, influence individuals' willingness to adopt AVs.

Harb *et al.* (2021) systematically analyzed studies about the impacts of AVs on travel behavior, focusing on SAE J3016 Levels 4 and 5. Their review examines five research methods: controlled trials, driving simulators/virtual reality, agent-based and travel-demand models, interviews, and field experiments. Users are reluctant to adopt AV technologies, with 19–68% reporting unwillingness to use them, although this resistance is expected to decline over time. The authors emphasize the need for further research on long-term impacts and business models, whether private or shared vehicles.

Bansal & Kockelman (2017) assessed the long-term adoption of autonomous and connected vehicle technologies based on 2,167 interviews with US residents, considering supply and demand dynamics, and price reductions. The average willingness to pay (WTP) for Levels 3 and 4 automation under the NHTSA classification was USD 5,550 and USD 14,580, respectively. Nevertheless, 39% of respondents were unwilling to pay for either driver-assistance or autonomous-driving features. Kockelman & Boyles (2018) also assessed the expected timelines for technological maturity by grouping technologies according to the NHTSA automation levels. Levels 3 and 4 were categorized as long-term technologies because their implementation requires the integration of multiple technological components and processing systems.

Income emerges as an important demographic determinant of willingness to pay for AVs. Rahimi, Azimi & Jin (2022) found that higher-income individuals in the United States are more likely to report greater WTP, whereas Jiang *et al.* (2021) identified a negative association between monthly income and WTP in China. These contrasting findings point to relevant regional and socioeconomic differences. Financial affordability was also identified as a barrier in a qualitative study involving German participants (Weigl, Eisele & Riener, 2022), with lower-income individuals consistently less inclined to pay a premium for AV technology.

Demographic characteristics, such as gender and age, remain important predictors of acceptance and WTP. Studies confirm the influence of both gender and age. Weigl, Eisele & Riener (2022) found that younger participants in Germany, up to 24 years old, were willing to pay significantly more for AVs than intermediate age groups, with no significant gender effect on WTP expressed as a percentage. However, Wadud & Chintakayala (2021) found that women are more likely to place greater value on AV ownership than men, whereas individuals above 56 years may be more likely to adopt shared mobility services in the United Kingdom. Education and vehicle ownership status indirectly influence WTP, often mediated by latent attitudes such as pro-multitasking and pro-technology attitudes (Rahimi, Azimi & Jin, 2022), reinforcing the complexity of adoption decisions.

Perceived safety is also a key factor, expressed through risk perceptions and concerns about trust in technology. Jiang *et al.* (2021) found that perceived risk has a limited influence on the acceptance of highly automated vehicles, whereas factors such as technological trust exert a stronger influence. However, Rahimi, Azimi & Jin (2022) caution that privacy concerns and limited trust in technology may outweigh favorable attitudes toward technological innovation, thereby reducing WTP.

These psychological factors interact with prior experiences and demographic profiles. Prior experience with technologies, whether regarding driving experience or broader attitude toward technology, has been shown to influence adoption. Jiang *et al.* (2021) show that driving experience positively affects WTP, whereas Rahimi, Azimi & Jin (2022) identify a pro-technology attitude characterized by interest in learning about and using new technologies as a positive predictor of WTP for AVs.

Kockelman *et al.* (2017) emphasize that, based on survey results from Texas, the transition to AVs will require a long period. Three barriers are particularly relevant: (a) the high cost of the technology, (b) fleet replacement rates given the average vehicle lifespan of 16.9 years in the United States, and (c) safety and privacy concerns. More than 55% of respondents would not pay extra for Level 3 or Level 4 automation under the NHTSA classification, 56.7% expressed concerns about the technology, and nearly 80% preferred to wait until the technology became more stable.

Kockelman et al. (2017) simulated annual technology cost reductions of 1%, 5%, and 10% to estimate the share of automated vehicles in the fleet by 2045, as reported in Table 2. Their results suggest that intermediate automation levels may represent transitional stages, with the fleet progressively shifting toward fully autonomous vehicles. Similar patterns were identified by Xie & Liu (2022) and Deichmann, Grosse-Ophoff & Kässer (2023).

Kyriakidis, Happee & de Winter (2015) surveyed approximately 5,000 respondents across 109 countries. Their results indicate that 22% of respondents were unwilling to pay for automation, whereas 33%

Table 2 • AV fleet shares in 2045, adapted from Kockelman *et al.* (2017)

Annual percentage reduction in technology prices	Automation levels (NHTSA)	Percentage share in the fleet
1%	L3	1.7%
	L4	3.4%
5%	L3	12.5%
	L4	15.9%
10%	L3	16.9%
	L4	38.5%

considered Level 5 automation highly desirable; moreover, 69% believed that Level 5 automation would reach 50% market penetration by 2050.

Schoettle & Sivak (2014) compared surveys conducted in China, India, Japan, United States, the United Kingdom, and Australia. Positive receptiveness toward AVs was highest in China and India, exceeding 85%. In the United States, the United Kingdom, and Australia, positive receptiveness was approximately 50%. Willingness to pay (WTP) was also higher in China and India, reaching up to US$8,000 in China. More than 65% of respondents in all six countries expressed concerns about sharing roads with non-autonomous vehicles.

Daziano, Sarrias & Leard (2017) conducted interviews with US respondents and found an average willingness to pay of US$3,500 for partial automation and US$4,900 for full automation. These recurring safety concerns and regional variations in WTP underscore the influence of regulatory and mobility contexts, extending adoption barriers beyond the individual level. WTP for AVs and their acceptance are linked to the regulatory context and to perceptions of a stable legal environment. Weigl, Eisele & Riener (2022) show that the establishment of a legal framework and government oversight of technological functionality are priorities for the public, which may foster trust and increase WTP.

Meanwhile, the availability and attractiveness of shared mobility services emerge as essential factors shaping WTP for AV ownership. Wadud & Chintakayala (2021) quantified the convenience of owning an AV as opposed to using automated ride-hailing services, revealing a preference for ownership. However, their study also identified an inconvenience cost associated with shared ride services, suggesting that WTP varies not only between ownership and rental but also across different service modalities. Rahimi, Azimi & Jin (2022) further support this relationship by demonstrating that daily users' willingness to pay for AVs is shaped by the perceived benefits of engaging in other activities while travelling, as well as by the availability of public transport and parking.

Recent reviews further inform that willingness to pay for AVs varies considerably across regional contexts and levels of economic development. Consistent with the findings of Schoettle & Sivak (2014), studies suggest that respondents in countries such as China and India have greater receptiveness to and willingness to pay for AVs than those in more mature markets, including the United States and Europe (Jiang *et al.*, 2021). These differences underscore the role of culture, socioeconomic conditions, and infrastructure in shaping AV acceptance. Although research conducted in developed countries, including Germany (Weigl, Eisele & Riener, 2022) and the United Kingdom (Wadud & Chintakayala, 2021) provides detailed evidence for these settings, willingness to pay and acceptance in emerging economies such as Brazil remain comparatively underexplored.

Despite significant advances in understanding the factors that affect AV adoption across diverse international contexts, the heterogeneity observed in existing findings underscores the critical need for studies that account for the specific characteristics of a country. The complex interactions among demographic, psychological characteristics, regulatory conditions, and infrastructure require further research to inform public policy and market strategies. To summarize this evidence, Table 3 presents the main findings of the studies discussed in this section.

Table 3 • Synthesis of the literature review based on user evidence

Reference	Location	Interviews	Highligths
Weigl, Eisele & Riener (2022)	Germany	32	Younger individuals (up to 24 years) willing to pay more; regulatory barriers and technological maturity are prioritized by the public.
Rahimi, Azimi & Jin (2022)	USA	1,019	Higher income is associated with greater WTP; concerns regarding trust and privacy outweigh pro-technology attitudes, reducing WTP.
Wadud & Chintakayala (2021)	United Kingdom	1,013	Women place higher value on AV ownership; older adults (>56 years) inclined toward shared mobility; inconvenience cost in shared services.
Jiang *et al.* (2021)	China	298	Monthly income has a negative impact on WTP in certain income groups; perceived risk has limited influence on the acceptance of highly automated AVs.
Harb *et al.* (2021)	multiple countries	not reported	Over 59% of respondents are not willing to pay for any AV feature. Studies reviewed indicate non-adopters of AVs range from 19% to 68%.
Kockelman *et al.* (2017)	Texas	1,364	Levels 1 and 2: between 23% and 45% of respondents would not be willing to pay anything for features associated with these levels. Over 55% of respondents would pay nothing for levels 3 and 4 (NHTSA).
Daziano, Sarrias & Leard (2017)	USA	1,260	Average user is willing to pay USD 3,500 for partial automation and USD 5,000 for full automation.
Bansal & Kockelman (2017)	USA	2,167	On average, 39% of respondents would pay nothing for driver support technologies or autonomous driving. Approximately 55% would not be willing to pay for Level 3 (NHTSA), and the same percentage would pay nothing for Level 4.
Kyriakidis, Happee & de Winter (2015)	109 countries	5,000	22% were not willing to pay anything for Level 5, but 33% considered this level highly desirable. 5% would pay over USD 30,000 for Level 5, and 20% were willing to spend USD 3,000. The estimate was that AVs would cost between USD 5,000 and USD 9,999 more. Intermediate levels of automation exhibit low willingness to pay for automation technology.
Schoettle & Sivak (2014)	China, India, Japan, USA, United Kingdom, and Australia	China: 610; India: 527; Japan: 585	Most respondents express concern about failures in driving systems. Regarding general opinion, approximately 50% hold very positive views in China and India, while in Japan 50% were neutral. Over 60% of respondents in all countries indicated concerns (high or moderate) regarding interaction with conventional vehicles. Over 75% of respondents are highly interested in full automation in China and India, a percentage much higher than in other countries. Except for China, most countries in the survey have a majority of respondents with low willingness to pay for AV features.
Casley et al. (2013), as cited by Kyriakidis, Happee & de Winter (2015)	Students at the University of Worcester	467	Over 71% would pay more than USD 5,000.

Table 4 • Implications and impacts of AV introduction, adapted from Milakis, Van Arem & Van Wee (2017)

Implications	Impacts	Possible scenarios and effects
First-order implications	Travel cost	Higher acquisition costs may constrain AV introduction. Travel time and generalized transport costs tend to decrease. Fuel savings due to fewer safety equipment requirements in vehicles. Benefits may be compromised if urban sprawl is induced, leading to longer travel times, higher fuel consumption, etc.
	Road capacity	AVs may have a positive impact on traffic flow capacity and stability, but benefits depend on adoption rates and higher levels of automation. Findings suggest that 10% capacity gains are only achieved with adoption rates exceeding 40%. Should demand increase, benefits may be compromised.
	Mode choice	Capacity gains may be followed by increased demand, and reduced generalized cost may encourage urban sprawl. Greater use of AVs may impact public transport and active modes of transport.
Second-order implications	Vehicle ownership and sharing	Reduction in vehicle ownership is a possibility. Sharing and rental services may reduce operational costs and may be more attractive than public transport.
	Location choice and land use	Possible impacts at the regional scale due to reduced travel time. Reduced demand for parking areas at destinations. Elimination of large parking areas, which may be converted into urban areas of interest.
	Transport infrastructure	Possible reductions in demand for circulation and parking areas; but benefits may be suppressed if there is an increase in travel. Possibilities of restricting public transport to denser urban areas, leaving low-density areas to be served by on-demand services.
Third-order implications	Energy consumption and air pollution	Possible reductions in GHG (Greenhouse Gases) emission volumes due to increased capacity, reduced vehicle weight, and electrification associated with automation
	Safety	Possibility of significant reductions in accident rates due to lower exposure to human error at higher levels of automation. At intermediate levels, risks associated with disengagement from driving may be significant
	Social equity	Possible significant impacts on lower-income populations due to the high costs of embedded technology in final vehicle prices.
	Economy	Impacts on urban property prices due to changes in travel times.
	Public health	Possible reductions in noise pollution and emissions, combined with lower accident rates and shorter travel times.

2.3. Public policy implications

The introduction and diffusion of vehicles equipped with automation technologies may have potential consequences at multiple levels, as discussed by Milakis, Van Arem & Van Wee (2017) and summarized in Table 4. These range from direct to indirect impacts, such as changes of property values in urban and suburban areas. In this context, public authorities are likely to implement mitigation, incentive, restriction, and other policy measures.

Overall, AV-oriented policies may generate considerable benefits; however, these gains could be limited by longer travel distances, increased reliance on private vehicles, modal shifts away from public transport and non-motorized modes, widening mobility inequalities, and the spatial dispersion of urban activities. These potential adverse effects provide a basis for identifying priority areas for public policy intervention over the coming decades. This context is further challenging due to the progressive introduction of automated vehicles over a transition period expected to span several decades.

3. Method

The introduction of vehicles with different levels of automation is assumed to rely on two main aspects: estimations of vehicle sales over time, both replacing exiting vehicles and introducing new ones to the existing fleet; and the availability of automation technologies. The first aspect is shaped by socioeconomic

Classification	**Automation levels**					
Proposed	Manual driving	Partial automation: alerts or driver assistance		Full automation: partial or fully autonomous driving		
SAE J3016	Level 0	Level 1	Level 2	Level 3	Level 4	Level 5
NHTSA	Level 0	Level 1	Level 2	Level 3	Level 4	

Figure 2 • Proposed grouping automation levels

factors, including GDP, population growth, and evolving mobility preferences, such as the declining interest in driving among younger people and the expansion of shared mobility. The second is defined by regulatory conditions, costs, and the maturity of the relevant technologies.

This section describes a model for simulating vehicle automation scenarios in Brazil until 2060. The model estimates the introduction and diffusion of passenger vehicles equipped with different levels of automation across the national fleet over the coming decades. Figure 2 summarizes the levels of vehicle automation defined by the SAE J3016 and NHTSA frameworks. These classifications distinguish between vehicles with no automation, those equipped with individual or combined driver-assistance functions, and those with partial or full automated driving. Together, these categories provide a consistent basis for the key technological distinctions relevant to the analysis of mixed-traffic conditions.

3.1. AV fleet share projection

The flowchart presented in Figure 3 summarizes the methodological framework adopted to estimate the vehicle fleet while accounting for the introduction of autonomous vehicles over the 2024–2060 horizon. The approach integrates historical data on the existing fleet, the new vehicles sold to replace scrapped ones, the growth rate of brand-new vehicles added to the fleet, and the ratio between the vehicle fleet and population (motorization rate). It combines time-series estimations and assumptions regarding vehicle scrappage, fleet renewal, and technological diffusion scenarios. Accordingly, the procedure incorporates three main components: the evolution of the existing vehicle fleet, the inclusion of new vehicles, and the adjustment of the fleet to match the expected total fleet estimated from population projections and motorization rates.

The baseline fleet is established using the observed time series from 2000 to 2023. The number of vehicles from the 2023 fleet remaining in operation between 2024 and 2060 is then estimated by accounting for vehicle scrappage, thereby representing the withdrawal of existing vehicles over time. In parallel, the model accounts for the number of new vehicles added to the fleet before 2023 and the associated historical fleet growth rate, calculated as the ratio of new vehicle registrations to the total fleet. This historical rate provides the basis for estimating the growth of new vehicle entries after 2023. In the flowchart, this component represents the projected inflow of new vehicles into the fleet throughout the analysed period.

Based on this projected rate, the post-2023 new vehicle fleet is estimated while accounting for the replacement of scrapped vehicles, including both new and older vehicles. Thus, the model not only estimates the inclusion of new vehicles but also considers that part of this inflow may correspond to the replacement of vehicles leaving the fleet through scrappage.

Subsequently, scenarios for the projected annual sales of automated vehicles (AVs) after 2023 are incorporated, considering only new vehicles. These scenarios make it possible to estimate the share of vehicles introduced annually that correspond to AVs. This procedure yields the projected share of AVs in the total fleet after 2023.

The flowchart also includes the projected motorization rate after 2023 in vehicles per inhabitant. When combined with the projected population, it allows the expected total fleet to be calculated from the population and from the motorization rate randomly sampled within the confidence interval of the projection. This result represents the total number of vehicles expected in each year, according to demographic and motorization trends.

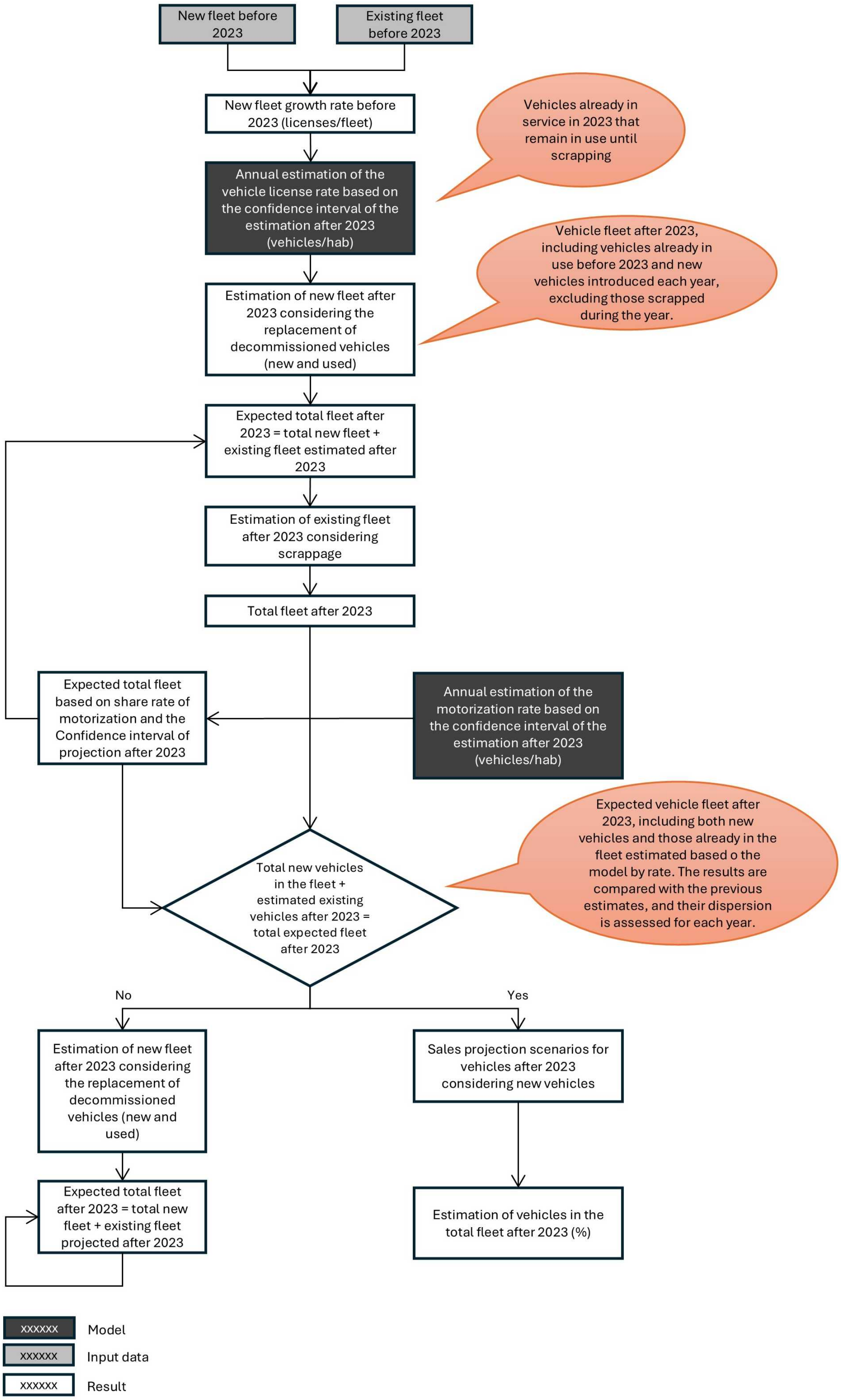

Figure 3 • Flowchart of the procedure for estimating the share of vehicles (passenger cars) with some level of automation

Next, this expected total fleet is compared with the post-2023 total fleet obtained by summing up the remaining existing fleet and the projected new fleet. The flowchart makes this verification explicit through the question: "New vehicles in the fleet + estimated existing vehicles after 2023 = total expected fleet after 2023?" This comparison is a consistency check between the two estimation pathways. When the values are considered close after rounding to the nearest integer, the results are deemed compatible, and the expected total fleet after 2023 is taken as equivalent to the sum of the projected new fleet and the projected existing fleet. When the values differ, a new projection is required to reduce the dispersion between the expected annual results.

Thus, the procedure combines the inventory of existing vehicles, new vehicle sales, scrappage, technological scenarios for AV adoption, and a consistency constraint based on the motorization rate. The result is an estimation of the total fleet and of the AV share that simultaneously represents fleet renewal dynamics and the expected motorization.

The procedure presented in the flowchart in Figure 3 was replicated 100 times. In each replication, the motorization rate and annual new-vehicle registration rate were randomly sampled from the confidence intervals of their respective time series through 2060. Each simulation produced annual estimates of the share of vehicles with some level of automation in the total fleet disaggregated by age interval: 0–5, 6–10, 11–15, 16–20, and more than 20 years. The results of the 100 replications were then aggregated to obtain the mean estimated share and corresponding standard deviation for each projection year and fleet-age interval.

To identify regional differences associated with socioeconomic conditions, three simulation scenarios were developed based on population and vehicle-fleet estimates over time: Brazil as a whole; the states in the South and Southeast regions (S/SE); and the states in the North, Northeast, and Center-West regions (N/NE/CW). For each scenario, the simulation generated annual estimates from 2024 to 2060 of the shares of vehicles with some degree of automation in the total fleet.

3.2. Estimation of new fleet and motorization rates

The growth rate of new fleet and motorization rates after 2023 were estimated by applying a Holt–Winters exponential smoothing time-series model with additive trend and seasonality for an annual series (Holt, 1957; Winters, 1960; Hyndman & Athanasopoulos, 2021). For an additive specification with seasonality of period m, the model is defined by Equations 1 to 3:

$$\ell_t = \alpha(y_t - s_{t-m}) + (1-\alpha)(\ell_{t-1} + b_{t-1}) \tag{1}$$
$$b_t = \beta(\ell_t - \ell_{t-1}) + (1-\beta)b_{t-1} \tag{2}$$
$$s_t = \gamma(y_t - \ell_t) + (1-\gamma)s_{t-m} \tag{3}$$

The h-step-ahead forecast is given by Equation 4:

$$\hat{y}_{t+h|t} = \ell_t + hb_t + s_{t+h-m} \tag{4}$$

where ℓ_t is the level, b_t is the trend, s_t is the seasonality component, and α, β and γ are the level, trend and seasonality parameters, respectively.

The confidence interval of the projection is obtained through bootstrap simulation of the residuals from the fitted model, as defined by Equation 5:

$$\tilde{y}^{(i)}_{t+h} = \hat{y}_{t+h|t} + \varepsilon^{*(i)}_{t+h} \tag{5}$$

where $\hat{y}_{t+h|t}$ denotes the point forecast from the Holt–Winters model, and $\varepsilon^{*(i)}_{t+h}$ represents a residual sampled with replacement from the historical fitted residuals. A total of 5,000 simulations were performed,

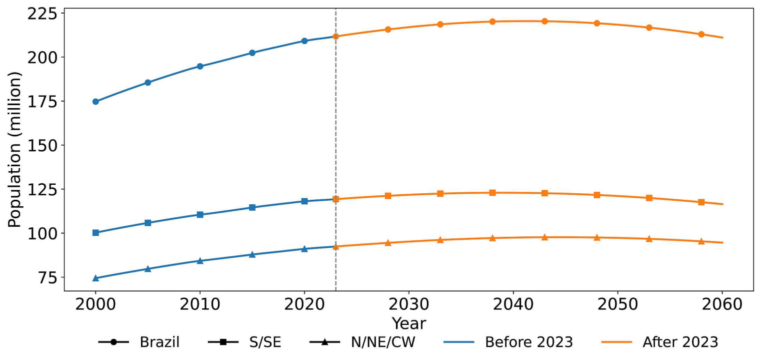

Figure 4 • Historical and projected population (million inhabitants), from IBGE (2024) population projections, 2024 revision

and the 95% confidence interval was obtained from the 2.5th and 97.5th percentiles of the simulated time series.

4. Results

4.1. Population, motorization rate, and vehicle registration rate estimations

The estimated population changes in Brazil and in the grouped regions S/SE and N/NE/CW were obtained from IBGE (2024) as shown in Figure 4. The historical data and projected values for automobile registrations and the circulating vehicle fleet in the Brazilian case are presented in Table 5 based on data provided by ANFAVEA (2024).

The time series of new vehicles and motorization rates were obtained for the 2024–2026 horizon using Holt–Winters exponential smoothing models with additive trend and seasonality. The parameters considered in the projections for Brazil and separately for the South/Southeast (S/SE) and North/Northeast/Central-West (N/NE/CW) regional groupings are presented in Table 6. These parameters were obtained through automatic fitting using a computational routine implemented with the Python `statsmodels.tsa.holtwinters` library, specifically the `ExponentialSmoothing` function. The time series for new vehicle rate was assumed to be the same at the national level and across the regional analysis scenarios for S/SE and N/NE/CW due to the absence of a regionally disaggregated historical series. The estimated time series are illustrated in Figures 5 to 8.

It should be noted that the motorization rate decreases over the planning horizon in both the national- and regional-level analyses. This occurs because the vehicle registration rate for new vehicles (Figure 5) is expected to remain broadly stable over time, notwithstanding seasonal fluctuations, whereas the population (Figure 4) is expected to increase until reaching a peak between 2040 and 2050, after which it begins to decline. In addition, the reduction in the motorization rate results from vehicle scrappage and the gradual removal of vehicles from the fleet over time, also resulting from a generational trend toward lower interest in new vehicle acquisition.

4.2. Parameters for AV sales estimation

Following the rationale by Lipson & Kurman (2017) and Litman (2021), it is assumed that the availability of vehicle automation technologies in countries such as Brazil will lag behind that of higher-income countries, thereby affecting the pace of AV introduction in the country. Hence, we adopted Litman's (2021) forecast for new vehicle sales as shown in Table 7.

The lowest percentages within the ranges proposed by Litman (2021) were adopted for each decade to account for the lag in technological availability between higher-income and developing countries. Three scenarios were simulated for the initial introduction of AVs in Brazil: 2025 for an accelerated scenario; 2030 for a moderate scenario; and 2035 for a conservative scenario. A five-year staggered deployment across automation levels was also assumed, beginning with the availability of vehicles with

Table 5 • Historical and projected registrations of new automobiles and automobile fleet (ANFAVEA, 2024)

	Fleet			Vehicle Registrations		
Year	Brazil	S/SE	N/NE/CW	Brazil	S/SE	N/NE/CW
2000	17,080,185	13,838,850	3,241,335	1,205,070	976,382	228,688
2001	17,797,010	13,363,578	4,433,432	1,318,232	989,846	328,386
2002	18,399,233	14,877,274	3,521,959	1,243,467	1,005,444	238,023
2003	18,865,467	15,216,893	3,648,574	1,215,549	980,462	235,087
2004	19,482,685	15,676,592	3,806,093	1,315,358	1,058,393	256,965
2005	20,217,943	16,216,960	4,000,983	1,439,822	1,154,892	284,930
2006	21,119,730	16,863,078	4,256,652	1,632,947	1,303,829	329,118
2007	22,445,951	17,839,504	4,606,447	2,085,706	1,657,669	428,037
2008	23,997,349	19,004,194	4,993,155	2,341,304	1,854,146	487,158
2009	25,817,430	20,338,374	5,479,056	2,643,862	2,082,773	561,089
2010	27,812,726	21,476,987	6,335,739	2,856,540	2,205,820	650,720
2011	29,811,473	22,948,872	6,862,601	2,901,647	2,233,688	667,959
2012	31,977,005	24,539,154	7,437,851	3,115,223	2,390,622	724,601
2013	34,017,474	26,023,368	7,994,106	3,040,783	2,326,199	714,584
2014	35,756,646	27,427,206	8,329,440	2,794,687	2,143,670	651,017
2015	36,765,902	28,094,320	8,671,582	2,123,009	1,622,277	500,732
2016	37,279,361	28,424,855	8,854,506	1,688,289	1,287,291	400,998
2017	37,897,466	28,838,552	9,058,914	1,856,584	1,412,791	443,793
2018	38,696,561	29,380,535	9,316,026	2,102,114	1,596,039	506,075
2019	39,591,508	29,988,287	9,603,221	2,262,073	1,713,390	548,683
2020	39,778,682	30,022,586	9,756,096	1,615,942	1,219,617	396,325
2021	39,847,584	29,985,852	9,861,732	1,558,467	1,172,768	385,699
2022	39,877,781	29,983,976	9,893,805	1,576,662	1,185,487	391,175
2023	39,986,756	30,022,283	9,964,473	1,721,400	1,292,437	428,963

Table 6 • Parameters of Holt-Winters exponential smoothing time series models with additive trend and seasonality

	Licensing rate	Motorization rate		
Parameter	All models (Brazil, S/SE, N/NE/CW)	Brazil	S/SE	N/NE/CW
m	9	9	9	9
α	1.0	1.0	0.0	0.3585
β	0.0	0.0	0.0	0.0
γ	0.0	0.0	0.0	0.0
ℓ_0	1.2742	2.1577	7.2070	2.3282
b_0	0.3770	−0.0802	−0.2534	−0.0952

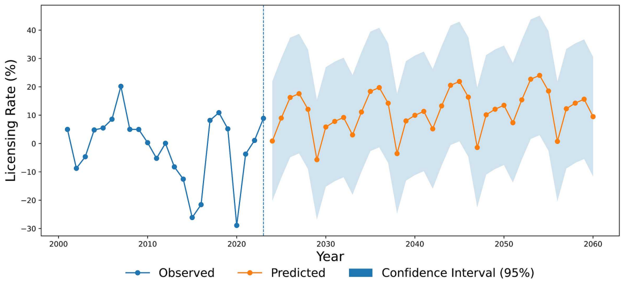

Figure 5 • Estimation of the licensing rate in Brazil, S/SE and N/NE/CO after 2023 with 95% confidence interval

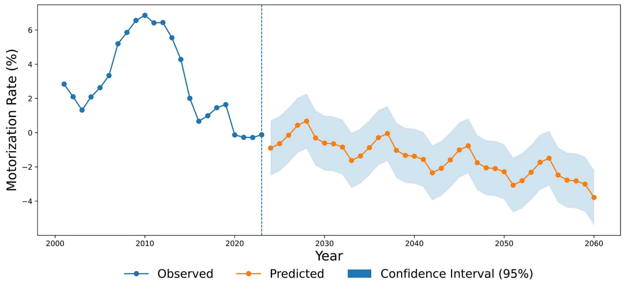

Figure 6 • Estimation of the motorization rate in Brazil after 2023 with 95% confidence interval

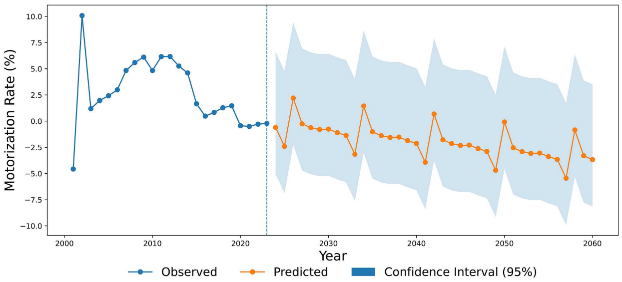

Figure 7 • Estimation of the motorization rate in S/SE after 2023 with 95% confidence interval

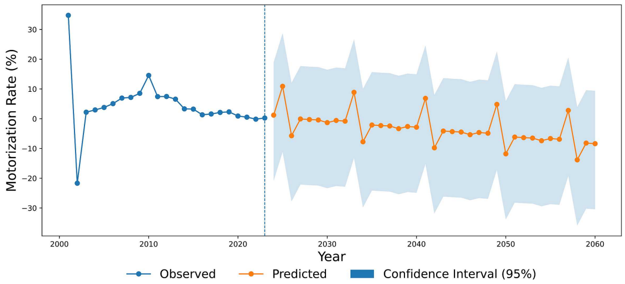

Figure 8 • Estimation of the motorization rate in NN/NE/CW after 2023 with 95% confidence interval

Table 7 • Prospects on the introduction of AVs (Litman, 2021)

Stage	Decade	New vehicle sales	Fleet	Travel
Development and testing	2020s	0%	0%	0%
Available at high prices	2030s	2–5%	1–2%	1–4%
Available at moderate prices	2040s	20–40%	10–20%	10–30%
Available at minimal prices	2050s	40–60%	20–40%	30–50%
Standard features included in most new vehicles	2060s	80–100%	40–60%	50–80%
Saturation (everyone who wants to own)	2070s	?*	?*	?*
Mandatory for all new and existing vehicles	?*	100%	100%	100%

* as per the original in Litman (2021)

partial automation (NHTSA Levels 1 and 2), followed five years later by full automation (NHTSA Level 3), and, finally, five years thereafter by an additional share of fully automated vehicles (NHTSA Level 4). This staggered deployment was intended to represent the progressive market availability of these technologies, assuming linear growth over time. The adopted percentages are reported in Table 8.

Although some features and technologies associated with partially automated vehicles are already available in Brazil, their adoption remains largely confined to luxury vehicles with high purchase prices and highly restricted market. Vehicles with Level 3 and Level 4 automation, according to the NHTSA classification, were initially treated separately in the sales projections, given that Level 4 automation entails substantial regulatory challenges. Accordingly, a five-year lag was assumed between the introduction of these two levels. They were subsequently grouped together to assess their share of the circulating vehicle fleet. Levels 1 and 2, in turn, were grouped under the category of partial automation for the simulation scenarios estimating fleet-share penetration. This distinction adequately captures the pattern identified by Xie & Liu (2022) and Deichmann, Grosse-Ophoff & Kässer (2023), who suggest that intermediate levels of automation tend to lose representativeness relative to both non-autonomous vehicles and vehicles with higher levels of automation.

The market-entry percentages for vehicles at each automation level were applied to annual forecasts of new vehicle registrations through 2060. From the first year of vehicle use onward, a scrappage model

Table 8 • Proposed scenarios for the introduction of automobiles with partial automation regarding new automobile sales

Year	Conservative	Moderate	Accelerated
2025			2%
2030		2%	11%
2035	2%	11%	20%
2040	11%	20%	30%
2045	20%	30%	40%
2050	30%	40%	60%
2055	40%	60%	80%
2060	60%	80%	100%

was incorporated to estimate the total circulating fleet of partially and fully automated vehicles as follows (Equation 6):

$$FVA_{la,t} = AV_{la,t} + (AV_{la,t} \cdot S_{t+1}) + \cdots + (AV_{la,t+n} \cdot S_{t+n}), \tag{6}$$

where $FVA_{la,t}$ is the total automobile fleet with automation level la in year t; $AV_{la,t}$ is the number of automobiles licensed with automation level la in year t; and S_t is the remaining fraction of automobiles after accounting for scrappage. The scrappage model is based on MCT (2010) as cited by La Rovere *et al.* (2016) and defined according to Equation 7:

$$S_t = 1 - \exp[-\exp(1.798 + 0.137t)]. \tag{7}$$

4.3. AVs sales estimation

Figures 9 to 11 present the estimated diffusion patterns under the conservative, moderate, and aggressive scenarios, respectively, for Brazil as a whole and for two regional groupings: the South and Southeast (S–SE) and the North, Northeast, and Central-West (N–NE–CW). The results are reported for NHTSA automation Levels 3–4, representing automated driving capabilities, and for the combined Levels 1–4. Levels 1–2, which encompass driver-assistance technologies, are not displayed separately but can be derived as the difference between the projected shares for Levels 1–4 and Levels 3–4.

More substantial shares of automated vehicles in the Brazilian fleet are expected to occur only after 2045, even under the accelerated scenario. In the conservative and moderate scenarios, adoption is further extended over time. Several additional insights emerge from the estimated shares of automated vehicles in the Brazilian passenger car fleet:

- The period between 2030 and 2045 represents a critical phase in the diffusion process, during which the adoption trajectories for all automation levels begin to exhibit sustained growth toward full fleet penetration.
- Between 2045 and 2050, vehicles equipped with Levels 3–4 automation, which enable increasingly autonomous driving functions, are projected to surpass Levels 1–2 vehicles in their share of the total passenger car fleet.
- The dispersion of the projected adoption shares, as measured by their standard deviations, increases over time and with market penetration for both Levels 1–2 and Levels 3–4, indicating greater uncertainty as the diffusion process advances.

Under the conservative scenario for Brazil (Figure 9), Levels 1–4 reach 48% of the total passenger car fleet by 2060, compared with 68% under the moderate scenario and 93% under the aggressive scenario. Levels 3–4 including partial or full autonomous driving reach considerably lower shares by 2060: 26%, 37%, and 53% under the conservative, moderate, and accelerated scenarios, respectively. Thus, autonomous driving reaches half of the total fleet only in the most promising scenario. In the other scenarios, the shares of Levels 3–4 remain below 40% in 2060. These estimations are considerably less

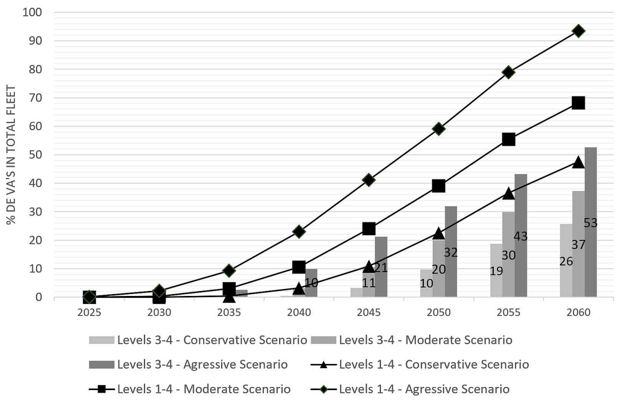

Figure 9 • Estimation of the share of vehicles with automation in the automobile fleet in Brazil

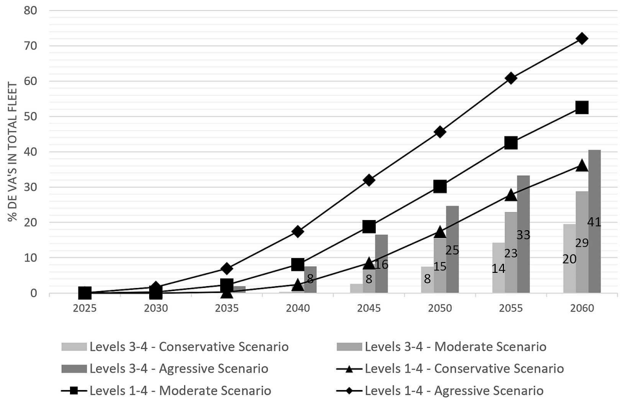

Figure 10 • Estimation of the share of vehicles with automation in the automobile fleet in the S and SE regions

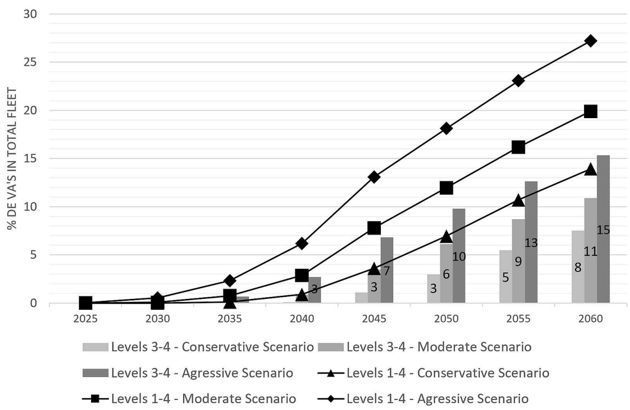

Figure 11 • Estimation of the share of vehicles with automation in the automobile fleet in the N, NE and CW regions

optimistic than those reported by Kyriakidis, Happee & de Winter (2015), in which 69% of respondents believed that Level 5 automation would reach 50% market share by 2050.

The regional estimates indicate a slower diffusion of automated vehicles across the Brazilian fleet. In the South and Southeast regions (Figure 10), the shares of vehicles at automation Levels 1–4 are projected to reach 36%, 53%, and 72% by 2060 under the conservative, moderate, and accelerated scenarios, respectively. Vehicles with higher levels of automation (Levels 3–4) are projected to account for 20%, 29%, and 41% of the fleet under the corresponding scenarios. Over a 20- to 25-year horizon, the combined share of Levels 3–4 remains below 25%, even under the aggressive adoption scenario. Vehicles at Levels 1–2 that provide driver-assistance functions account for up to 21% of the fleet under the aggressive scenario but remain below 15% under the conservative and moderate scenarios.

In the North, Northeast, and Central-West regions (Figure 11), the share rates are considerably lower, reaching only 27% of the fleet by 2060, even under the accelerated scenario. For Levels 3–4, such rates under the conservative, moderate, and accelerated scenarios are 8%, 11%, and 15%, respectively. Over a 20-year projection horizon, the results for Levels 1–4 only slightly exceed 10% under the accelerated scenario.

Table 9 compares the estimates obtained in this study with those reported by Deichmann, Grosse-Ophoff & Kässer (2023) and Kockelman *et al.* (2017) under alternative diffusion scenarios. The simulated share of fully automated vehicles estimated is substantially lower than the 2035 rates calculated by Deichmann, Grosse-Ophoff & Kässer (2023), which range from 17% under the conservative scenario to 37% and 57% under the baseline and accelerated scenarios, respectively. Kockelman *et al.* (2017) estimated comparatively more moderate adoption rates for Level 3 and Level 4 vehicles by 2045, at 12.5% and 15.9%, respectively, under the assumption that the cost of embedded technologies would reduce by 5% annually.

Table 9 • Comparison of the share of AVs Levels 3 and 4 (%)

Scenario	2030	2035	2040	2045
Kockelman et al. *(2017) (total fleet)*				
1% technology price reduction	4	5	6	5
5% technology price reduction	10	16	20	29
10% technology price reduction	25	37	48	55
Deichmann, Grosse-Ophoff & Kässer (2023) (automobile fleet)				
Delayed	4	17		
Baseline	12	37		
Accelerated	20	57		
Simulated model (automobile fleet)				
Conservative	0	0	0	3
Moderate	0	0	3	11
Aggressive	0	3	10	21

Recent evidence from commercial automated taxi services reinforces the need for a conservative interpretation of these estimations. Waymo One in Phoenix, Arizona, is one of the most mature autonomous ride-hailing operations in the United States and remains geographically constrained and dependent on a relatively limited fleet, specialized sensor-maintenance infrastructure, and the Waymo Driver software platform Rosa *et al.* (2023, 2025). Even within this technologically advanced and high-income context, persistent technical limitations have required extensive testing and validation across millions of simulated and real-world miles to reduce perception and operational failures. Deployment also faces regulatory and institutional constraints, requiring sustained coordination with public authorities. Comparable experiences involving Waymo in San Francisco, California, and Baidu in Beijing suggest that, despite substantial technological progress, commercial deployment remains spatially restricted and has yet to achieve large-scale diffusion.

These constraints, including deployment within controlled operational domains, small fleet sizes, and reliance on complex networks of technological and operational partners, provide additional support for conservative diffusion scenarios for Brazil. In this context, comparatively limited technological, institutional readiness and economic and regulatory constraints may further limit adoption at scale. Accordingly, the ranges reported in Table 9, which are lower than those estimated by Deichmann, Grosse-Ophoff & Kässer (2023) and Kockelman *et al.* (2017) , appear more consistent with the available empirical evidence. These findings also highlight the need for long term planning that explicitly accounts for the coexistence of multiple automation levels within heterogeneous vehicle fleets.

Taken together, the estimations show that the diffusion of automated vehicles in the Brazilian fleet occurs progressively, yet remains clearly uneven across automation levels, market scenarios, and regional contexts. In all cases analyzed, vehicles with partial automation may advance earlier and in larger proportions than fully automated vehicles, sugggesting that the technological transition is likely to unfold through successive stages rather than through marked replacement of the conventional fleet.

The comparison of the conservative, moderate, and accelerated scenarios shows that, although the shares vary according to the assumptions adopted, fully automated vehicles do not become prevalent by 2060. This pattern is further supported by the regional analysis, which indicates faster adoption in the South and Southeast than in the North, Northeast, and Central West. These differences are consistent with the regional variation in motorization patterns, fleet renewal rates, and socioeconomic conditions considered in the model. In this context, Table 9 provides a particularly relevant synthesis, showing that the shares of Level 3 and Level 4 vehicles remain limited throughout the study period. The results therefore suggest that the Brazilian fleet will continue to be characterized by the coexistence of conventional and partially automated vehicles, alongside a comparatively small share of fully automated vehicles, for an extended period.

5. Conclusions

This paper describes a modeling framework for assessing the introduction and diffusion of automated vehicles within the Brazilian automobile fleet under substantial technological, regulatory, and market uncertainty. The results obtained from a simplified model show that the introduction of autonomous vehicles in Brazil will require at least another 25 years to reach a significant share of the circulating fleet and generate benefits such as increased traffic capacity, reduced travel times, and improved overall road safety. Given that the benefits associated with autonomous driving, such as reductions in average delay and travel times, are generally linked to fleet penetration rates above 50% (Atkins, 2016), the results suggest that this threshold would only be reached at the end of the analysis horizon, in 2060, and exclusively under the aggressive scenario.

Under the conservative scenario, fully automated vehicles account for 10% of Brazil's passenger-car fleet after 25 years, whereas their share rises to 32% under the accelerated scenario. When all four automation levels are considered jointly, the estimated shares are naturally higher, reaching half of the fleet within the same period under the accelerated scenario, while remaining comparatively limited under the conservative and moderate scenarios. By 2060, automated vehicles will represent a substantial proportion of the fleet, particularly under the moderate and accelerated scenarios. Nevertheless, aggregating automation levels provides limited insight into the operational implications of fleet composition and into the conditions under which vehicles with different levels of automation would coexist and interact within the transport system.

The results suggest that the automated vehicle share of the Brazilian fleet is likely to increase gradually. Partial automation is expected to expand more substantially, whereas fully automated vehicles may retain a limited market share through 2060, with marked variation across national and regional scenarios. Accordingly, the policy, regulatory, and planning implications should not be interpreted primarily as responses to a large-scale technological transition. Rather, they underscore the need to prepare for an extended period in which conventional vehicles coexist with those comprising different levels of automation. Such preparation will require the incremental development of regulatory frameworks, clearly defined safety and liability standards, infrastructure strategies designed for heterogeneous traffic conditions, and policy measures that account for the regional disparities likely to influence the spatial and temporal diffusion of automated vehicles in Brazil.

The framework developed still requires further refinement, for example, with respect to assessing Brazilian consumers' willingness to pay for the new technologies required for automation. Another perspective for future development concerns more robust investigations of the correlations between the socioeconomic indicators and the annual volume of licensed passenger cars. Studies addressing other vehicle types, such as light and heavy trucks and buses, could also reveal different results.

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CRediT authorship contribution statement

Alexandre Rodrigues Seixas: Conceptualization, Data curation, Formal analysis, Methodology, Validation, Writing – original draft, Writing – review & editing; *Claudio Luiz Marte*: Conceptualization, Methodology, Project administration, Validation, Writing – original draft, Writing – review & editing; *Cassiano Augusto Isler*: Methodology, Validation, Writing – review & editing; *Edvaldo Simões da Fonseca Junior*: Validation, Writing – review & editing; *Leopoldo Rideki Yoshioka*: Validation, Writing – review & editing.

Use of artificial intelligence-assisted technology

The artificial intelligence tool ChatGPT was used to write the paper exclusively for grammatical correction and stylistic editing. The authors assume full responsibility for the use of the tool.

Competing interests statement

No competing interests have been declared with regard to this paper or its contents.

Data availability statement

The data, models, and code supporting the findings of this study may be made available by the corresponding author, Alexandre R. Seixas, upon request.

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