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CCAMERAS
Moving towards the future

Report on scenario assumptions and their economic background

Deliverable 4.2

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Table of abbreviations

Abbreviation	Full Form
AI	artificial intelligence
AT	autonomous trucks
AV	automated vehicles
CAGR	compound annual growth rate
CAPEX	capital expenditure
CCAM	Cooperative, Connected and Automated Mobility
CGE	Computable General Equilibrium
EU-27	European Union of 27 Member States
EU SBS	European Union Structural Business Statistics
MaaS	mobility as a service
NACE	nomenclature of economic activities
OPEX	operating expenditure
TCO	total cost of ownership
L1, L2, L3, L4, L5	SAE automation levels

Introduction

The CCAM-ERAS project develops robust, evidence-based methods to assess the employment impacts of Cooperative, Connected and Automated Mobility (CCAM) deployment. It supports strategic planning through scenario analysis and impact evaluation. This deliverable contributes to the 4th WP of this project.

The objectives of WP4 are threefold:

1. to study the impact of CCAM on employment by sector and employment in occupations and provide a short, medium- and long-term employment forecast (aggregate of direct, indirect, and induced effects) of different investment and adoption pathways of CCAM,
2. to provide improved understanding of the short, medium and long-term effects of CCAM on the demand for new and updated skills, and
3. to analyse employment effects of CCAM across the full value-chain.

The modelling within CCAM-ERAS will provide the employment effects of CCAM deployment in Europe using Cambridge Econometrics' E3ME model. The forecast acts as an early information sign on the evolution of employment in the logistics, warehousing, freight and passenger transport. This exercise will involve building the baseline (business-as-usual scenario) and then describing the different pathways of CCAM adoption and the underlying investments.

E3ME is a computer-based model integrating the global economy, energy systems, and the environment. Originally developed under the European Commission's research framework programmes, it is now widely applied across Europe and internationally for policy assessment, forecasting, and academic research.

E3ME is frequently employed to evaluate the economic, labour market, and environmental impacts of policy interventions. Its structure explicitly links economic activity with the energy system, ensuring internal consistency across all domains. Unlike CGE models, E3ME is demand-driven and does not assume that markets always clear through price adjustments. This fundamental difference has significant practical implications: regulation and other policies can lead to increased output where spare economic capacity exists.

In this deliverable, the adoption rates of CCAM technologies serve as the primary driver of modelling outcomes. Variations in adoption influence investment levels, operational costs, and changes in supply chain relationships, which are then incorporated into E3ME to assess macroeconomic and societal impacts. The result of the modelling is the estimation of employment effects across countries and sectors, encompassing not only direct employment impacts from CCAM deployment, but also indirect and induced impacts—through supply-chain linkages and broader macroeconomic interactions.

The adoption rates of CCAM are differentiated by region, imposing, for example, differential speeds of adoption across regions to model their impacts on the national and EU-wide economy and its labour markets.

The deliverable is structured as follows. Next chapter discusses the baseline assumptions, while third chapter presents the assumptions for the three scenarios to be modelled. The last two chapter summarise the common assumptions.

Baseline scenario (Business-as-usual)

In this chapter, the baseline (business-as-usual scenario) to CCAM deployment adoption is described. The baseline is defined as the future in which no substantial technological transformations occur in the transport and warehousing sectors. The supply chain of these sectors, represented in the model through its input-output structure, is assumed not to suffer any substantial change. Likewise, there are no assumptions about changes to the sectors' labour intensity, capital expenditure (CAPEX) or operational expenditure (OPEX).

In conclusion, the baseline simulates a business-as-usual future, in which the characteristics of the transport and warehousing sectors are the same as those implied in historical data.

The following sectors were chosen to understand CCAM deployment pathways: electronics, motor vehicles, electricity, land transport, warehousing, telecommunications, and computer services. Additionally, no new changes to the regulatory and legislative barriers are assumed.

Employment

Between 2025 and 2050, the baseline scenario for employment in key EU-27 sectors reflects a modest but consistent evolution in line with projected output growth and structural shifts in the economy. Across the period, the share of employment attributed to each sector, expressed as a percentage of total EU-27 employment, provides insights into their relative economic importance and labour demand trends.

Land transport and motor vehicle manufacturing is expected to maintain steady significance. Land transport, covering road, rail, and pipelines, increases its employment share from 3% in 2025 (6.19 million people) to 3.3% by 2050 (6.40 million people), driven by moderate growth in freight and passenger mobility. Similarly, the motor vehicle manufacturing sector, fuelled by transitions to electric and automated vehicles, sees its employment share grow from 1.4% in 2025 (2.78 million) to 1.6% by 2050 (3.14 million), reflecting sustained demand despite automation.

Warehousing, essential for long-haul freights as well as last-mile logistics and supply chains, gradually rises from 1.4% in 2025 (2.93 million) to 1.9% by 2050 (3.61 million), underlining its strategic role in a digitalised, service-oriented economy. Meanwhile, electricity, a relatively stable sector which is needed for the green transition, maintains a modest growth from 0.5% in 2025 (1.02 million) to 0.7% in 2050 (1.42 million). Although the sector benefits from energy transition investments, automation limits its labour intensity.

Technology-related sectors exhibit notable dynamism. Computer services is forecast to see a consistent rise in employment share, from 2.0% in 2025 (4.07 million) to 2.6% by 2050 (5.03 million), as digitalisation, AI deployment, and software development expand. Telecommunications is projected to increase slightly from 0.4% in 2025 (0.91 million) to 0.7% in 2050 (1.28 million), maintaining a steady presence amid evolving infrastructure needs. Electronics, foundational for automation and digital infrastructure, will remain relatively stable at 0.6% in 2025 (1.13 million) and 0.7% by 2050 (1.42 million), with limited employment fluctuation.

Table 1: EU-27 Employment, 2025-2050 (thousand people)

Year	2025	2030	2040	2050
Total	205,746	205,072	199,468	194,936
Electronics	1,133	1,210	1,325	1,421
Motor vehicles	2,785	2,973	3,061	3,136
Electricity	1,016	1,125	1,237	1,415
Land transport	6,187	6,394	6,467	6,404
Warehousing	2,929	3,102	3,367	3,610
Telecommunications	911	992	1,132	1,276
Computer services	4,074	4,317	4,733	5,029
Share in total employment				
Electronics	0.6%	0.6%	0.7%	0.7%
Motor vehicles	1.4%	1.4%	1.5%	1.6%
Electricity	0.5%	0.5%	0.6%	0.7%
Land transport	3.0%	3.1%	3.2%	3.3%
Warehousing	1.4%	1.5%	1.7%	1.9%
Telecommunications	0.4%	0.5%	0.6%	0.7%
Computer services	2.0%	2.1%	2.4%	2.6%

Source: E3ME baseline, derived from Cedefop Skills Forecast 2025.

Output

Between 2025 and 2050, the baseline scenario for EU-27 sector output shows consistent, moderate growth. Total sector output increases from approximately EUR 26.5 trillion in 2025 to over EUR 37.1 trillion by 2050.

Computer services output is expected to rise from EUR 642 billion in 2025 to over EUR 1.04 trillion by 2050, supported by ongoing digital transformation, cloud computing, and AI integration. Its output share is expected to increase steadily from 2.4% to 2.8%. Telecommunications also grows steadily, increasing from EUR 437 billion in 2025 to nearly EUR 665 billion in 2050, with a relatively stable output share of 1.7% to 1.8%.

Motor vehicle manufacturing sees strong growth, rising from EUR 912 billion in 2025 to nearly EUR 1.36 trillion by 2050, despite pressures from decarbonisation and European Green Deal commitments. Its share of total sector output rises from 3.4% to 3.7%.

Land transport, encompassing road and rail freight and passenger services, also grows significantly, from EUR 599 billion in 2025 to EUR 951 billion by 2050, with its output share increasing from 2.3% to 2.6%. This reflects rising mobility needs and improved freight efficiency.

Warehousing output increases from EUR 501 billion in 2025 to over EUR 767 billion in 2050, with its output share climbing from 1.9% to 2.1%, driven by e-commerce, just-in-time delivery, and the expansion of regional logistics hubs.

Electricity output expands more modestly, from EUR 484 billion in 2025 to EUR 621 billion by 2050, with its share slightly decreasing from 1.8% to 1.7%. Efficiency improvements and automation temper growth, despite the sector's centrality to the energy transition.

Electronics output rises steadily, from EUR 298 billion in 2025 to EUR 416 billion by 2050, maintaining a consistent 1.1% share throughout.

Table 2: EU-27 sectoral output - million 2010 EUR (2025-2050)

Year	2025	2030	2040	2050
Total (sum of all sectoral output)	26,473,513	28,384,613	32,166,498	37,069,672
Electronics	298,430	322,616	367,247	415,953
Motor vehicles	912,033	1,006,143	1,160,975	1,358,145
Electricity	484,040	528,884	570,531	621,365
Land transport	598,514	667,045	803,673	950,614
Warehousing	500,648	547,468	645,578	766,720
Telecommunications	437,101	477,188	561,787	665,333
Computer services	642,277	707,063	858,445	1,036,744
Share				
Electronics	1.1%	1.1%	1.1%	1.1%
Motor vehicles	3.4%	3.5%	3.6%	3.7%
Electricity	1.8%	1.9%	1.8%	1.7%
Land transport	2.3%	2.4%	2.5%	2.6%
Warehousing	1.9%	1.9%	2.0%	2.1%
Telecommunications	1.7%	1.7%	1.7%	1.8%
Computer services	2.4%	2.5%	2.7%	2.8%

Source: E3ME baseline using published sources.

Energy use

Between 2025 and 2050, total final energy demand in the EU-27 declines steadily, falling from approximately 1.40 million kilotonnes of oil equivalent (ktoe) in 2025 to around 1.01 million ktoe by 2050. This reduction reflects an average annual decline of around –0.9%, driven by increased efficiency, electrification, and sectoral shifts.

Within transport, energy consumption patterns shift markedly. Road transport, the dominant mode, sees its energy demand decrease from 209 million ktoe in 2025 to 145 million ktoe by 2050. Its share of total final energy demand falls slightly over the period, from 15.0% in 2025 to 14.3% by 2050. Rail transport experiences modest but consistent growth in energy use, increasing from 6.7 million ktoe in 2025 to 7.9 million ktoe by 2050. Its share of total energy demand rises from 0.5% to 0.8%.

Electrification plays a critical role in transforming energy use due to the EU-27 wide commitments to the Green Deal targets to be reached by 2050. Total electricity demand in the EU-27 rises from 233 million ktoe in 2025 to over 328 million ktoe by 2050, indicating deeper integration of electricity across sectors.

Electricity use in road transport is expected to surge from 5.5 million ktoe in 2025 to 50.9 million ktoe by 2050 as fleets are replaced with increasingly green alternatives reliant on clean energy. Its share of total electricity demand increases from 2.4% to 15.5%. Rail transport electricity use is also expected to grow steadily, from 5.6 million ktoe in 2025 to 7.6 million ktoe by 2050, maintaining a stable 2.3% share by 2050 also to meet the investments in the European investments in TEN-T rail networks.

Table 3: EU-27 total energy demand (thousand toe)

Year	2025	2030	2040	2050
Total	1,395,452	1,289,400	1,122,590	1,010,398
Rail transport	6,695	6,796	7,265	7,860
Road transport	209,465	197,552	167,096	144,677
Share				
Rail transport	0.5%	0.5%	0.6%	0.8%
Road transport	15.0%	15.3%	14.9%	14.3%

Source: E3ME baseline using published sources.

Table 4: EU-27 electricity demand (thousand toe)

Year	2025	2030	2040	2050
Total	233,491	257,590	293,732	328,387
Rail transport	5,556	5,999	6,893	7,595
Road transport	5,539	12,992	37,406	50,875
Other transport services	746	746	746	745
Share				
Rail transport	2.4%	2.3%	2.3%	2.3%
Road transport	2.4%	5.0%	12.7%	15.5%
Other transport services	0.3%	0.3%	0.3%	0.2%

Source: E3ME baseline using published sources.

Consumption

The EU-27 consumption baseline pathway reflects forecasted long-term shifts in sectoral output, driven by decarbonisation, efficiency improvements, and evolving demand structures. Between 2025 and 2050, total sector output is forecasted to grow from approximately EUR 7.13 trillion to nearly EUR 9.95 trillion (in constant 2010 euros).

Petrol-related consumption in sectors are projected to undergo a substantial contraction. Output is forecasted to decline by over 58%, falling from EUR 372 billion in 2025 to just EUR 155 billion by 2050. As a share of total economic output, petrol drops from 5.2% to just 1.6%, reflecting a significant systemic shift away from fossil fuel reliance in line with the Member States' commitments and decarbonisation targets under the European Green Deal.

In contrast, rail transport and other non-air transport sectors are projected to experience steady growth. Rail transport output increases by over 41%, from EUR 58.9 billion in 2025 to EUR 83.3 billion in 2050, while maintaining a constant 0.8% share of total economic output. This stable share amid rising output underscores the EU-27's strategic alignment with the TEN-T Rail investments, promoting sustainable mobility goals and ongoing electrification of infrastructure.

Table 5: EU-27 sector output - million 2010 EUR (2025-2050)

Year	2025	2030	2040	2050
Total	7,125,931	7,634,424	8,641,141	9,949,800
Petrol	372,461	330,604	218,973	154,802
Rail transport	58,974	63,879	73,361	83,294
Other transport (excludes air transport)	50,253	55,218	64,413	73,954
Share				
Petrol	5.2%	4.3%	2.5%	1.6%
Rail transport	0.8%	0.8%	0.8%	0.8%

Source: E3ME baseline using published sources.

Scenarios

In this chapter, the different CCAM use cases are discussed in more detail, by first going over a brief review of the literature, a narrative of automation in that use case, and the assumptions tied to the use case, with a differentiation by sensitivity (high uptake, medium uptake, low uptake). Each use case will be a different scenario in the E3ME model.

Warehousing

Literature

The adoption of CCAM technologies in the warehousing sector is shaped by several sectoral characteristics. Automation within the warehousing and logistics sectors reflects a broader technological shift in allocating tasks between labour and capital. Labour-related expenses, including wages, overtime, training, and staff turnover, can account for as much as 65% of total warehouse operating costs (Dey, 2025). Coupled with persistent labour shortages, these cost pressures have become a key catalyst for the accelerated adoption of automation technologies (Dueholm et al., 2024; Sharma & Zhang, 2022).

Further, this sector is expected to see strong growth in automation, mainly due to the expectation that regulatory hurdles are likely to be minimal. Since warehousing operations typically occur on private property, public land-use constraints do not apply, reducing the likelihood of regulatory pushback concerning CCAM technology applications. By 2030, it is projected that over 51% of warehouses globally will have deployed automation technologies such as CCAM (Research and Markets, 2024). Dey (2025) anticipates that 73% of warehouse operators will implement automation by 2027. This marks a notable rise from the 25% adoption rate recorded in 2024 (Meteor Space, 2024; Schranner & Fischer, 2025), which itself represented a substantial increase from just 5% in 2014.

The task-based framework developed by Acemoglu and Restrepo (2019) provides insights into these dynamics by emphasising the "task content of production". This framework aims to explain how tasks are divided between human workers and machines during production, highlighting the significant reallocation of tasks from labour to capital due to automation. The authors conclude that while automation enhances production efficiency, it is likely to reduce the number and share of non-automated jobs, including in the warehousing and logistics sectors. However, while automation offers potential efficiency gains, the sector's low profit margins make the initial costs of automation a significant barrier.

Moreover, in the context of this automation framework, it is expected that wage growth will not keep pace with the productivity gains resulting from automation (Acemoglu & Restrepo, 2021). Savushkin (2024) further supports this, pointing out that automation in warehousing and logistics is reshaping employment, reducing the need for human involvement in core processes. Companies such as Amazon exemplify this shift by transitioning workers from manual tasks to roles involving robot supervision (Berkers et al., 2023). Savushkin (2024) argues that while this can elevate skill requirements, it also creates stress, demotivation, and fear of job loss among employees, with 29% of logistics workers worldwide fearing replacement by machines (Lambrechts et al., 2021), and up to 47% of current jobs are considered at risk (Loske, 2022).

These findings are representative of the expectations of labour input reductions and productivity gains of the literature. Fully automated warehouses are estimated to reduce labour costs by up to 65% (Supply Chain Council of European Union, 2020), while simultaneously increasing productivity by between 25% and 70% (Roland Berger, 2016b).

Savushkin (2024) further highlights that automation often leads to monotonous, less fulfilling roles for remaining staff, who now perform tasks robots cannot, with little to no compensation for their changing duties. Moreover, the authors point out that businesses face challenges in adopting automation, particularly around workforce readiness, high investment costs, and uncertainty. Employers increasingly seek workers with higher digital skills, creating a social divide between those able to upskill and those left behind in the evolving labour landscape (Nantee & Sureeyatanapas, 2021).

These concerns highlight an important barrier to adoption, which is the presence of strong labour unions. It is expected that they will continue to influence the pace and nature of CCAM integration by advocating for job security and worker reskilling. A related barrier to CCAM adoption lies in digital infrastructure and skills availability. Integration into broader, increasingly digital supply chains is critical, but uneven levels of automation across industries can limit compatibility and slow uptake. As a result, the future trajectory of CCAM in warehousing depends not just on cost and regulation, but also on the alignment of workforce skills and the broader ecosystem's digital readiness.

A final barrier to adoption in the warehousing industry is that the investment requirements for warehouse automation vary substantially based on the extent of automation pursued. Basic automation solutions designed to assist in picking operations may require an investment as low as USD 50 000, whereas the development of fully automated warehouse systems can entail costs of up to USD 25 million (Ocado, 2025).

Narrative

Based on the literature, the warehousing sector is expected to experience the most significant uptake of automation out of the three use cases by 2050. While traditionally constrained by low profit margins, which pose challenges in offsetting the high upfront costs of automation, the sector benefits from a relatively low resistance path to implementation. This is largely because warehousing automation occurs on private land, avoiding the complex legislative hurdles associated with public space technologies. Other specific use cases, such as truck and bus depots, are set to experience automation deployment starting in 2027.

However, potential hurdles to this high automation uptake exist. As mentioned in the literature review, labour unions remain influential in this domain, and the anticipated pushback could slow the uptake of CCAM in this sector.

Labour reskilling and shortages could also play a significant role in slowing down this transition, with the higher-skilled labour being more expensive and in relatively lower supply, which may impose operating restrictions on automation in warehousing.

Further, as discussed previously, full integration of automated warehousing systems into supply chains could be hindered if automation uptake remains limited in other sectors. In such cases, a lack of compatibility across systems could restrict the overall diffusion of CCAM technologies.

Nevertheless, the sector's closed environment and targeted operational needs make it a prime candidate for advanced automation.

Assumptions

Three cases were considered, reflecting different degrees of deployment challenges and/or resistance that the different use cases might encounter. Specifically, a high uptake scenario, a medium uptake scenario, and a low uptake scenario for the deployment of CCAM were considered.

Adoption rate

Automated warehousing solutions are expected to experience important growth over the next years. By 2030, at least 51% of all warehouses worldwide will have implemented some level of automation (Research and Markets, 2024). Further, the automated warehousing segment is forecasted to reach USD 55 billion by 2030, with an annual growth rate of 18.7% from 2024 (Grand View Research, 2024c). This expected growth in the automated warehousing market could be tied to growth in the overall warehousing market. Drawing on these data points, adoption rate assumptions for warehousing were assumed through to 2050. The data from Grand View Research (2024b) informed the high uptake path, whilst the data from Research & Markets (2024) informed the construction of the low uptake path. The medium uptake scenario follows a naïve, linear path of adoption defined by the historical trends recorded by the literature (Meteor Space, 2024; Schranner & Fischer, 2025). Recognising that the growth projections may not fully account for potential adoption barriers, such as regulatory measures within the EU or opposition from organised labour, adjustments have been made accordingly. Specifically, considering these moderating factors, the timelines associated with the growth rates have been extended to reflect three distinct adoption assumptions. Under the high uptake scenario, the 2030 target is postponed to 2035; and for the low uptake, to 2045. The corresponding growth rates are detailed in Table 6 below.

Table 6: The annual growth rate (CAGR) of automated warehouse market share by level of uptake

Adoption uptake	Source	CAGR	Horizon
High	Grand View Research (2024b)	9.85%	2035
Medium	Historical trends	4.32%[1]	N/A
Low	Research & Markets (2024)	3.45%	2045

Source: Cambridge Econometrics.

As can be seen in Table 7, it can be expected that automated warehousing, which made up around 25% of the warehousing sector in 2024, will saturate the market by 2050 in the most optimistic case (high uptake)[2]. In cases where the hurdles described in the previous section are more challenging to overcome, it could be expected that automated warehouses will reach 75% market share by 2050, based on a naïve linear growth of the historical adoption patterns. In the most conservative case, where the hurdles to adoption are assumed to be the most important, automated warehousing is still projected to capture 60% of the market share by 2050.

Table 7: Automated warehousing share assumptions by level of uptake

Year	Low uptake	Medium uptake	High uptake
2024	25%	25%	25%
2030	30.65%	37%	43.93%
2040	43.04%	56.25%	100%
2050	60.44%	75%	100%

Source: Cambridge Econometrics.

To identify the share of the warehousing and logistics (H52) sector covered by the use cases,

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[1] This sensitivity extrapolates the historical trends recorded by Schranner & Fischer (2025) and Meteor Space (2024) linearly up to 2050.

[2] The year at which saturation is achieved is 2039.

a share profile of the warehousing and support activities for transportation sub-sectors was estimated using EU SBS data. The sub-sectors of interest are warehousing and storage (H5210), service activities incidental to land transportation (H5221), and service activities incidental to water transportation (H5223).

Investment costs

Investment costs of automation in the warehousing sector capture many different factors, ranging from the size and operations of a warehouse (pick-up and drop off, loading, packaging, and spatial configuration), to the intensity of automation (automation as human augmentation, or full automation as human replacement). Taking these factors into account, Ocado (2025) provided an estimation of the automation costs of an average-sized warehouse for different automation intensities, ranging from USD 50 000 to USD 25 million, depending on the level of automation. Based on this data, a benchmark figure of USD 10 million is assumed for modelling. Since labour costs are expected to decline but not disappear, the second highest cost range of warehouse automation proposed by Ocado (2025) was selected, corresponding to semi-automation. That category specifies costs ranging from USD 5 million to USD 15 million. The average value for the assumed automation cost for an average warehouse in the USA was selected. That value was then adjusted to reflect the average warehouse size in Europe of 11 000 square meters (CBRE, 2022b). Thus, assuming that the average cost of building an 11 000 square meter warehouse is around USD 9.5 million[3], it is estimated that the automation of warehouses will cost around USD 5.9 million, representing a 62% increase versus the baseline cost.

Productivity gains

The automation of warehouses is likely to generate cost savings. In a review of use cases of automated solution, Roland Berger (2016b) estimated that automation led to productivity increases between 25 to 70% due to higher output and efficiency resulting from automation. Due to the nature of the productivity gains estimates, it is assumed that productivity gains from automation would be the average of the gains observed in the use cases, which would be 45%[4].

Road freight transportation

Literature

Automation is fundamentally reshaping employment dynamics within the freight transport sector. Mirroring developments in warehousing and logistics, the advent of autonomous vehicles is altering the distribution of tasks between human labour and machines (Acemoglu & Restrepo, 2019). This transformation is largely propelled by the need to mitigate supply chain disruptions, address persistent labour shortages, and meet increasing demand for rapid and reliable delivery services (Clements & Kockelman, 2017; McQuaide, 2025).

While automation brings considerable economic advantages, such as reducing logistics costs by up to 40% (McQuaide, 2025), it also poses a substantial threat to traditional employment, particularly among truck drivers and warehouse operatives. The widespread adoption of autonomous trucks, for instance, has the potential to displace between 2 million and 4.4 million truck driving jobs in Europe and the USA by 2030 (Kilcarr, 2017). As such, the majority of anticipated cost savings from automation in the freight transport sector is expected to stem from reduced wage expenditure (Clements & Kockelman, 2017). Further, Oxford Economics projects a contraction of approximately 9% in US transport and warehousing employment by 2030 (Oxford Economics, 2019).

This is also supported elsewhere in the literature, as CCAM is anticipated to have transformative impacts on the driving workforce (Beede et al., 2017; Groshen et al., 2019),

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[3] This is calculated based on the average size of warehouses in Europe and the average price of construction in square meters (CBRE, 2022a; Compass International, 2023).

[4] In the three uses cases reviewed by Roland Berger (2016b), productivity gains of up to 25% were observed in the first case, up to 70% in the second, and up to 40% in the third. The average computed is the flat average of these ceiling estimates.

impacting occupations ranging from truck, ride-hailing, taxi, bus, and delivery service drivers (Yankelevich et al., 2018). Forecasts about the development of autonomous trucks (ATs) in the United States indicate that truck platooning with only a driver in the leading vehicle will appear between 2022 and 2025, AT fleets without drivers will start running on interstate highways between 2025 and 2027, and ATs without drivers from loading to delivery on all types of roads will appear as early as 2027 (Chottani et al., 2018). The persistent shortage of workers in truck driving occupations (IRU, 2023) can have two broad impacts: improving the attractiveness, and accessibility of the occupation or hastening the adoption of ATs to overcome the challenge of finding workers.

However, while automation displaces certain roles, it is likely also going to generate new opportunities, particularly in higher-skilled positions that require expertise in robotics, artificial intelligence, and systems management (McQuaide, 2025). As repetitive and manual tasks are increasingly handled by machines, the workforce is expected to shift towards more technical roles. According to McQuaide (2025), new job categories are emerging in areas such as AI system design, data analysis, fleet automation oversight, and warehouse robotics programming. Moreover, the integration of advanced technologies necessitates continuous monitoring, troubleshooting, and optimisation, responsibilities that can only be fulfilled by skilled professionals.

Similarly, significant cost reductions are anticipated in the road freight sector. According to Kelkar et al. (2024), automation in long-haul freight transport could lower the total cost of ownership by approximately 42%, primarily due to reduced expenditure on labour-intensive tasks such as driving and loading/unloading. For shorter-distance operations (up to 250 miles), cost reductions are more modest, around 13%, but still largely driven by labour savings. Over time, these cost dynamics are expected to enhance the profitability of autonomous freight transport. Kelkar et al. (2024) suggest that despite the high initial investment required for technologies such as AV kits, remote monitoring systems, and vehicle enhancements, these costs are offset by ongoing savings in fuel, repairs, and driver wages. Furthermore, as the technology continues to mature and economies of scale are achieved, the cost of automation hardware and software is expected to decrease. This development is also likely to improve operational efficiencies, contributing to enhanced profitability.

The adoption of automated trucks is generally characterised by a two-phase return-on-investment trajectory (Roland Berger, 2016a). In the medium term, corresponding to automation Levels 1 to 3, increasing capital investments per vehicle lengthen payback periods, while operational savings remain relatively stable. During Levels 1 and 2, driver-assisted platooning on long-haul routes exceeding 2,000 miles can yield payback periods of 13 and 37 months, respectively. However, by Level 3, the payback period extends to 66 months, with financial viability dependent on achieving platooning rates above 90% of total mileage. In the longer term, return on investment improves markedly. At Level 4, payback time is reduced to 28 months, driven largely by further reductions in driver-related costs. By Level 5, where full automation is achieved, the payback period contracts significantly to just 4 months, indicating the transformative potential of advanced CCAM technologies for cost-efficiency in freight transport.

Fuel savings represent another major source of cost reduction in automated freight transport. Automation facilitates improved fuel efficiency through optimised driving behaviours, minimised idling, and enhanced route planning. Reported fuel savings range from a minimum of 10% to a maximum of 27% (Gehm, 2019; Self Drive News, 2023). Consistent with this, Lee et al. (2023) concluded in their review of the literature that fuel savings from automated trucks fall broadly within a 10-40% range. These efficiencies are attributed to consistent eco-driving practices, including strategic acceleration, braking, and coasting, that alone can reduce fuel use by up to 9.5% (Thijssen et al., 2014). Further gains of between 9% and 17% may be realised by maintaining optimal motorway speeds (Aurora, 2024). Additionally, AI-based route optimisation contributes to reduced fuel consumption by limiting engine idling and the incidence of empty miles (Villano, 2025).

Forecasts on the deployment of autonomous trucks (ATs) cover a wide range. On the more optimistic side, truck platooning with only a driver in the leading vehicle (Level 4) could appear as soon as 2025, and AT fleets without drivers (Level 5) will start running on interstate highways by 2027. Fully automated freight transport from loading to delivery on all types of roads may appear as early as 2027 (Chottani et al., 2018). On the other hand, more conservative estimates see a gradual shift towards full autonomy over the 2027-2040 period (Kelkar et al., 2024). In this case, the automated freight truck deployment timeline is expected to start with driverless operations (Level 4) on highways and between transfer hubs. At that stage, Kelkar et al., (2024) expect manual drivers to continue handling trailers to and from transfer hubs, while autonomous trucks manage the long-haul leg. The authors conclude that due to these factors, the more challenging environment (e.g., curvier roads, tunnels) and operational specificities (e.g., shorter average routes), automated trucks will likely only represent about 4% of the European truck fleet by 2035. However, the adoption of lower levels of automation proceeds at pace in the freight industry. Frost & Sullivan (2020) states that Level 1 autonomous freight trucks accounted for 45% of the fleet in 2020, and Level 1 and 2 trucks are expected to represent 88% of the truck fleet in Europe and North America by 2040.

Narrative

The uptake of automation technologies in the freight sector is expected to differ across its market segments. Based on the findings of the literature and the mature application of CCAM technologies, automation is expected to start earliest and experience the highest levels of uptake by 2050 across the long- and medium-haul segments.

However, the last-mile delivery sub-sector of freight presents notable challenges. Experts suggest that automation in this segment is unlikely in the European context due to geographic and regulatory complexities. Issues such as navigating diverse urban environments, safety concerns, and the need to access private property limit the feasibility of full automation. As a result, while core freight operations are on a clear path toward automation, last-mile delivery is expected to remain largely manual in the future, with automation playing only a marginal role in this segment.

Due to these different uptake rates and the very limited CCAM application expected in last-mile delivery, it is expected that automation will be important, but less than in the warehousing sector.

Assumptions

A similar structure to that of the warehousing use case was set out here. Three cases were considered, reflecting different degrees of deployment challenges and/or resistance that the different use cases might encounter. Specifically, a high uptake scenario, a medium uptake scenario, and a low uptake scenario for the deployment of CCAM in freight were considered.

To disentangle private commercial transportation (e.g., taxis) from public passenger transportation from freight road transportation in the land transport sector (H49), their relative sizes was be approximated using EU Structural Business Survey (SBS) data, more specifically turnover by mode of transportation, which would allow for a rough estimation of the share of passenger vs freight road transportation.

Adoption rate

According to industry experts, the adoption of CCAM technologies in the freight sector is expected to advance steadily, particularly in long and medium-haul transport, where automation is projected to begin as early as 2025. Labour union resistance is expected to be minimal in this sector, reducing social friction and enabling smoother integration of automated systems.

This is consistent with Kelkar et al. (2024), who argue that the timeline for automated freight truck deployment is expected to start with driverless operations (Level 4) on highways and between transfer hubs. At that stage, the authors expect manual drivers to continue handling trailers to and from transfer hubs, while autonomous trucks manage the long-haul leg.

Level 4 autonomy involves driverless operations, with transfer hubs needed for recharging or refuelling. This shift to full autonomy is expected to occur gradually from 2027 to 2040 (Kelkar et al., 2024). Due to topographical challenges (curvier roads, snow, and tunnels) and operational hurdles (shorter routes, on average), the authors expects at most that high level automated trucks will represent around 4% of the truck fleet by 2035. Like in the case of

warehousing automation, it is assumed here that these estimates do not account for external challenges, and the timeframe of adoption is thus adjusted depending on the sensitivity to reflect that. Further, it is assumed that these vehicle types have a 2025 market share of 0.25%, reflecting the developments of pilot projects such as Einride (2024) throughout Europe. Similarly, it is assumed that the deployment of last-mile delivery starting in 2030, will account for 1% of last-mile delivery solutions that year (
Table 10). This is to reflect the likely role that the Covid pandemic played in accelerating the uptake of automated proximity delivery systems such as drones (World Economic Forum, 2020).

Lower levels of automation are expected to grow rapidly in the forecast period. Under the most enabling circumstances, low automated freight trucks (up to L3), would grow to around 95% of the market by 2043, before declining to around 85% in 2050 in light of growth in the L4/L5 segment. The more conservative baseline scenario, constrained by regulatory and societal factors, projects an 88% penetration rate by the end of the forecast period. The highest share is achieved in the medium scenario, where low automated trucks make up around 95% of the market by 2050. The scenarios are anchored in estimates provided by Frost & Sullivan (2020), who anticipate that autonomous trucks will comprise roughly 88% of the European fleet by 2040, up from an estimated 45% market penetration rate in 2020.

Based on the literature and expert feedback, it is expected that highly automated long- and medium-haul trucks will see the start of the deployment of highly automated vehicles in 2025, with the uptake of CCAM in last-mile delivery being severely delayed due to the high barriers to the technology in Europe. To reflect the high barriers to adoption in last-mile delivery, it is assumed that uptake of CCAM in this case will start in 2035, 10 years after road freight transportation. The resulting shares in adoption can be observed in Table 8,
Table 9, and
Table 10, respectively.

Table 8: Highly automated (L4/L5) road freight share assumptions by level of uptake

Year	Low uptake	Medium uptake	High uptake
2025	0.25%	0.25%	0.25%
2030	0.42%	0.47%	0.57%
2040	1.17%	1.66%	2.89%
2050	3.26%	5.84%	14.75%

Source: Cambridge Econometrics based on Kelkar et al. (2024).

Table 9: Low automated (up to L3) road freight share assumptions by level of uptake

Year	Low uptake	Medium uptake	High uptake
2025	50.32%	51.46%	53.21%
2030	56.27%	58.85%	62.93%
2040	70.37%	76.95%	88.00%
2050	88.00%	94.16%	85.25%

Source: Cambridge Econometrics based on Frost & Sullivan (2020).

Table 10: Automated last mile delivery share assumptions by uptake level

Year	Low uptake	Medium uptake	High uptake
2035	1%	1%	1%
2040	1.20%	1.29%	1.37%
2050	1.73%	2.14%	2.57%

Source: Cambridge Econometrics based on Grand View Research (2024a).

Investment costs

A recent study by, with Kelkar et al. (2024) estimated that automated trucks cost up to USD 100 000 more than their non-automated counterparts. Earlier, Roland Berger (2016a) estimated the incremental cost of automation, from levels 1 through 5. To gauge the current incremental cost of automation of road freight, the share profile of the Roland Berger (2016a) costs were used to disaggregate the Kelkar et al. (2024) estimates, yielding a current estimate of the incremental cost levels profile, which is presented in the table below. The table depicts the additional cost of automation to progress from one level to the next.

To gauge how much relative to a non-automated truck this automation cost would represent, it is estimated that a new, non-automated truck costs about USD 110 000 (BAS World, 2025; Hargreaves, 2024; IDTechEx, 2024). Based on this figure, full automation would represent an increase of around 90% in investment costs.

Table 11: Assumptions on the incremental cost profile by automation level of trucks, USD

Category	L1	L2	L3	L4	L5	Total
Share	7.69%	21.79%	26.50%	25.21%	18.80%	100%
Total	7,692	21,795	26,496	25,214	18,803	100,000
Hardware	2,061	5,840	7,099	0	0	15,000
Software	5,631	15,955	19,396	25,214	18,803	85,000

Source: Cambridge Econometrics based on Kelkar et al. (2024), Roland Berger (2016a).

Roland Berger (2016a) argue that these investment costs split roughly 85% to software and 15% to hardware. The authors also expect that hardware investments finish at the automation level L3, with software advances needed to progress to L4 and L5 subsequently.

Due to the legal issues laid out in the narrative section, it is assumed that automated last-mile delivery in Europe will only use road-based vehicles (no sidewalk robots). For these delivery vehicles, investment costs can be gleaned from the total costs of ownership estimated by Levkovych & Saraceni (2023). They compared the costs for a Standard diesel delivery van, an electric van, and a road-based autonomous delivery robot of the Neolix company. Based on their data, it can be assumed that an autonomous delivery robot costs around EUR 30 000, around 6% cheaper than a standard diesel delivery van, which makes it a competitive alternative to standard delivery vehicles.

Cost savings

Kelkar et al. (2024) argue that the automation of freight road transport would result in significant cost savings for the operator. The authors argue that automated trucks are expected to reduce the total cost of ownership for long-haul trucks by about 42%, with most of the savings coming from labour-intensive driving and (un)loading tasks. For trucks operating shorter distances of up to 250 miles, the cost savings are smaller (13%), but still fall predominantly on labour-intensive activities. This reduction in savings achieved continues, such that the authors conclude that autonomous trucks covering fewer than 100 miles are unlikely to be profitable (i.e., TCO increases vs non-automated alternative).

These cost savings dynamics are likely to influence the profitability of autonomous freight road transportation over time. According to Kelkar et al. (2024), autonomous freight vehicles operating on long routes of over 1,500 miles are expected to be profitable. Although initial capital expenditures are high, covering AV kits, remote monitoring, and enhanced vehicle systems, Kelkar et al. (2024) argue that these costs would be offset by savings on driver wages, fuel, and repairs.

Kelkar et al. (2024) argue that as hardware and software costs fall and operations become more efficient, profitability is expected to increase over time.

Labour costs are assumed to remain unchanged for the first levels of automation, up to level 3, as the driver is still required to operate the vehicle. At Level 3, drivers are expected to take control only occasionally, such as in emergencies, which may reduce fatigue. Although longer shifts might be technically feasible, stakeholders agreed shift regulations would remain unchanged (International Transport Forum, 2017). As a result, any labour savings from conditional automation are likely to be modest and assumed to be no more than 10%. The bulk of labour savings would come in at later levels of automation, starting around level 4, where some studies have estimated the levels of saving cost reduction at around 79% (L.E.K. Consuting, 2022). Finally, driver costs could be completely at level 5, further reducing labour costs, which would increase labour cost saving to a ceiling of around 90%, with the remaining labour costs mainly incurred by remote oversight operators (Engholm et al., 2020; Roland Berger, 2016a).

Further, labour costs are expected to decline with automation. It is assumed that labour costs in Europe represent 35% of the total cost of ownership (International Transport Forum, 2017). Elsewhere, automation might also lead to a reduction in insurance costs, which represent around 5% of total costs (L.E.K. Consuting, 2022). Automated freight vehicles have the potential to reduce insurance costs by reducing the occurrence of accidents. Approximately 95% of all road traffic accidents are caused by human error (European Parliament, 2019). CCAM technologies have the potential to minimise freight driver error significantly, reducing accidents and insurance payouts. This would lead to insurance cost savings of around 5% to 10% (World Economic Forum, 2021).

Table 12: Assumptions on cost savings by level of automation

Difference from L0	L1	L2	L3	L4	L5
Labour costs			-10%	-79%	-90%
Insurance costs				-5%	-5%

Source: Cambridge Econometrics based on World Economic Forum (2021), International Transportation Forum (2017), Roland Berger (2016a).

Cost savings are expected to grow with the deployment of highly automated vehicles. According to Roland Berger (2016a), the adoption of automated trucks typically progresses through two distinct phases. In the medium term (Levels 1 to 3), payback periods increase markedly at each stage, driven by rising per-vehicle investment costs while operational savings remain relatively constant. During Levels 1 and 2, the benefits of driver-assisted truck platooning on long-haul routes exceeding 2,000 miles enable relatively swift returns on investment, 13 months and 37 months, respectively. However, by Level 3, the payback period extends to 66 months, underscoring the critical role that platooning intensity plays in determining financial viability. Achieving a payback period of under three years at this stage is only feasible when platooning accounts for more than 90% of total mileage.

In the longer term, the return on investment dynamics improve significantly. Level 4 sees a notable reduction in payback period (28 months), primarily driven by additional savings in driver-related costs. By Level 5, where full automation is realised, the payback period contracts sharply to just 4 months, highlighting the transformative cost-efficiency potential of advanced autonomous freight operations.

For last mile delivery, the difference in costs between standard diesel delivery vehicles and their alternatives can be observed in **Error! Reference source not found.** below.

Table 13: Added total cost of ownership of electric and autonomous last mile delivery by cost type (EUR)

Cost	Difference to diesel van
Purchasing cost	-6.07%
Subsidies and Indirect initiatives	-6.07%
Registration fee	0.00%
Road tax	-78.87%
APK inspection	-32.69%
Energy costs	-92.76%

Insurance cost	-50.01%
Maintenance and repair	-63.46%
Labour cost	-100.00%
TCO for 8 years	-85.18%

Note: for enegy costs, it is assumed that the energy content of diesel is 10 kWh/L (36MJ/L).
Source: Cambridge Econometrics based on Levkovych & Saraceni (2023), The Engineering ToolBox (2008).

Although the TCO per vehicle seems very favourable to the autonomous alternative, it should be stressed that the autonomous delivery robot has important limitations. According to Levkovych & Saraceni (2023), due to its much smaller cargo volume and slower delivery speed, the autonomous vehicle variant is the least profitable option, with a net revenue per km of EUR 8.3 vs EUR 11.03 for a diesel van. Since profitability here depends on the cargo pace and average parcel size, this dynamic is assumed to remain stable over time. A full breakdown of the cost-benefit analysis conducted by the authors is available in the table below.

Table 14: Cost-benefit analysis of diesel, electric, and autonomous last-mile delivery

Indicator	Diesel (Renault)	Electric (Renault)	Autonomous (Neolix)
Delivery volume per year (units)	132,880	132,880	124,254
Delivery kilometer per year (km)	78,000	78,000	103,131
Parcels per kilometer delivered (units)	1.7	1.7	1.2
Income per parcel delivered (EUR)	7	7	7
Income per kilometer (EUR)	11.93	11.93	8.43
Cost per kilometer (EUR)	0.9	0.96	0.13
Net Income per kilometer (EUR)	11.03	10.96	8.3

Source: Cambridge Econometrics based on Levkovych & Saraceni (2023).

Fuel savings

The transition to automated freight road transport solutions is expected to generate important fuel savings.

Automation in freight trucking can lead to substantial fuel efficiency gains through optimised driving behaviour, reduced idling, and improved route planning. Autonomous trucks have demonstrated fuel savings of at least 10%, with some cases showing improvements of up to 27% (Gehm, 2019; Self Drive News, 2023). These efficiencies are largely achieved through consistent eco-driving techniques, such as strategic acceleration, braking, and coasting, which have been shown to reduce fuel consumption by up to 9.5% (Thijssen et al., 2014). Additionally, maintaining optimal motorway speeds can result in further savings of between 9% and 17% (Aurora, 2024). Automation could also help reduce unnecessary fuel use by minimising engine idling and lowering the number of empty miles travelled, thanks to AI-driven route optimisation (Villano, 2025).

Based on this literature, fuel savings generated by automation in freight transport at large and in last-mile delivery are assumed to be 10%.

Passenger transportation

Literature

Timelines for CCAM adoption in passenger transport follow a similar pattern. Pilot projects for CCAM in passenger transport began in 2010, with structured government initiatives appearing by 2021-2022. These pilots primarily tested level 3 automation, where vehicles can manage driving tasks under specific conditions but require a hu-man to intervene when necessary (Wadud, 2017). Wider deployment is expected to begin around 2030, with Level 3 and Level 4 automation expanding in public and private fleets. Level 4 technologies could account for up to 50% of fleet size by 2050 (Concas et al., 2021), with Level 5 autonomy entering the market more fully between 2035 and 2067, depending on region and regulatory alignment (Lavasani et al., 2016; Yu & Chen, 2021). This overlapping timeline indicates a phased transition: earlier levels of automation will lay the groundwork, technically, socially, and economically, for more advanced autonomous systems, supported by targeted investments from sectors such as software, manufacturing, and public administration (Tirachini & Antoniou, 2020). The timeline for deploying CCAM in passenger transport is less conclusive than in other sectors, driven largely by concerns of passenger safety, trust, and regulations. For example, stringent regulations in the EU are seen as a barrier to innovation in CCAM. Unlike the more supportive conditions in places like the United States, the European policy landscape hinders market entry for established CCAM providers from outside Europe, such as Waymo (Laura Babio, 2023).

Filippi et al (2023) offer a meta-review of studies investigating how automation technologies affect employment at different level of analysis. The results are often inconsistent and inconclusive since only few clear results emerge and the impact of automation technologies is unclear for many levels of analysis.

In passenger transport, CCAM technologies also promise considerable cost savings. Several studies suggest that automated fleets could complement and enhance existing public transport systems at significantly lower operating costs than traditional fixed-route services. In many public transport systems in the Global North, driver salaries constitute 45% to over 60% of operational costs (Alcorn & Kockelman, 2020; American Public Transit Association., 2020; Litman, 2024). As technology advances, the drive to optimise public transport costs is expected to progressively reduce, and ultimately eliminate, driver-related expenditures. Experts have proposed that current fixed-route bus services could evolve into dynamic ride-sharing (DRS) networks composed of autonomous vehicles, offering both economic and service-level advantages (Brownell & Kornhauser, 2014).

In addition to cost reductions, CCAM deployment in passenger transport is anticipated to deliver substantial energy savings. Through optimised driving, congestion mitigation, and enhanced vehicle efficiency, studies estimate fuel consumption reductions between 30% and 90%, depending on the level of automation, vehicle type, and operational conditions (Future Agenda, 2020). Automated public transport systems, particularly those employing driverless buses, may benefit further from coordinated vehicle flows and reduced idle times, supported by digital infrastructure such as 5G. These advancements contribute not only to operational cost reductions but also to broader goals related to sustainability and environmental impact.

Narrative

Passenger transport represents the slowest and most complex pathway for CCAM adoption in the EU. While small-scale pilots, particularly for public automated transport, have begun in countries such as France, Germany, Norway, and Finland, widespread deployment is not expected before 2035. Private automated passenger vehicles face even steeper hurdles.

The EU’s AI Act and associated vehicle legislation currently restrict AV deployment to Level 2 or Level 3 automation, with Level 3 permitted only on highways. These limitations, combined with rigorous safety and cybersecurity standards, make mass-market penetration of higher automation levels unlikely before 2040. The situation is further complicated by the cross-border nature of private travel, which requires consistent legal acceptance of automated vehicles across all Member States, a condition that does not currently exist and is unlikely to materialise soon.

In this context, it is expected that highly automated private vehicles may emerge in the medium term (10+ years) as premium offerings, targeted at niche segments. However, these are projected to remain marginal, with market penetration unlikely to exceed 1%.

Other market segments present a comparatively more favourable outlook. Initial deployment of CCAM technologies in passenger transport is expected to occur within the Mobility as a Service (MaaS) space, for instance through the introduction of robotaxis. Public transport also represents a promising area for adoption; however, potential societal resistance could result in slower uptake compared to the MaaS segment.

Assumptions

Adoption rate

The timeline for deploying CCAM technologies in passenger transport remains less defined compared to other sectors, primarily due to persistent concerns around passenger safety, public trust, and regulatory complexity. Insights from industry stakeholders suggest that growth in this market will likely vary significantly across different segments.

The earliest adoption is anticipated within the Mobility as a Service (MaaS) segment, particularly in the deployment of robotaxis. These services typically operate within clearly defined geographic boundaries (e.g., urban areas), which simplifies operational challenges. Moreover, the potential for substantial labour cost savings, coupled with ongoing driver shortages, presents strong incentives for early implementation. Although some experts foresee the introduction of highly automated robotaxis within the next two to four years, local opposition and regulatory delays could push widespread deployment as far out as 2035.

In the realm of public transport, a similar trajectory is expected, with initial deployments likely to occur between 2027 and 2028. Here too, operational predictability and limited geographical scope serve as enablers of early adoption.

By contrast, the outlook for fully automated private passenger vehicles is considerably more uncertain. The inherently cross-border nature of private vehicle use necessitates a high degree of legal harmonisation across EU Member States, something that is currently lacking and unlikely to be resolved in the short term. This legal fragmentation, combined with enduring concerns over safety and data protection, presents a significant barrier to large-scale deployment. Nonetheless, some experts have argued that such vehicles could initially find a foothold within the premium automotive segment, with manufacturers potentially offering early models from 2027 onwards. However, it is not expected that this niche will break 1% of market share by 2050. In line with this, automated, non-commercial private passenger transportation is not modelled, as laid out in the use cases defined by WP3C.

Overall, while MaaS and public transport applications are expected to lead the way in CCAM adoption, the trajectory for private passenger vehicles remains constrained by structural and regulatory challenges.

The literature on this topic seems to align with the view provided by the industry stakeholders. Pilot projects for CCAM in passenger transport began in 2010, with structured government initiatives appearing by 2021-2022. These pilots primarily tested level 3 automation, where vehicles can manage driving tasks under specific conditions but require a human to intervene when necessary (Wadud, 2017). Wider deployment is projected to begin around 2030, with Level 3 and Level 4 automation expanding in public and private fleets. Level 3 systems are expected to be deployed in large numbers across public transport (Future Agenda, 2020; Wadud, 2017). In an optimistic case, Level 4 technologies could account for up to 50% of the fleet size by 2050 (Concas et al., 2021), with Level 5 autonomy entering the market more fully between 2035 and 2067, depending on region and regulatory alignment (Lavasani et al., 2016; Yu & Chen, 2021). This overlapping timeline indicates a phased transition: earlier levels of automation will lay the groundwork, technically, socially, and economically, for more advanced autonomous systems, supported by targeted investments from sectors such as software (J-62), manufacturing (C-29), and public administration (O) (Tirachini & Antoniou, 2020).

As a whole, experts believe passenger transportation will likely see the first rollouts before 2030, with an acceleration of uptake after that date.

Based on this literature, the following adoption rates are assumed for public and private commercial passenger transportation, which can be observed in the table below. To reflect the more favourable regulatory environment towards public transportation, an adoption rate of 1% was set for the initial year of deployment there, whereas that figure stands at 0.5% for private commercial passenger transportation.

Table 15: Highly automated (L4/L5) passenger transportation market share by level of uptake

Transportation type	Year	Low uptake	Medium uptake	High uptake
Public	2027	1%	1%	1%
Public	2030	1.29%	1.34%	1.41%
Public	2040	3.02%	3.54%	4.37%
Public	2050	7.07%	9.35%	13.57%
Private	2027	0.50%	0.50%	0.50%
Private	2030	0.66%	0.69%	0.72%
Private	2040	1.66%	1.97%	2.47%
Private	2050	4.17%	5.65%	8.46%

Source: Cambridge Econometrics based on Litman (2024).

Investment costs

AV production costs for private vehicles and rideshare platforms are high, with recent estimates by Riggs and Richardson (2024) estimating that the total AV hardware cost (not including the base vehicle) lies at around USD 92 000 per unit. This cost would come on top of the base vehicle cost. The authors estimate this using a Waymo standard vehicle (Jaguar I-PACE), priced at around USD 75 000, for a total AV cost estimate of around USD 167 000. Due to the similar vehicle characteristics (size, weight), it can be assumed that the vehicle automation cost for public transportation, such as buses, mirrors that of freight transportation depicted in Table 11. An analysis conducted by ING estimated the price of diesel buses to be around EUR 200 000 – 250 000. Based on this data, it is assumed that the benchmark price for the average public transit bus system in Europe costs around EUR 225 000 (~USD 247 500). Automation would thus in this case lead to a 40% increase in costs, assuming automation costs amount to USD 100 000 (**Error! Reference source not found.**).

Cost savings

Some studies contend that CCAM fleets can enhance the offering of existing public transport servers at a fraction of the operational costs associated with traditional fixed-route services. In many systems, public transport vehicle drivers are the most expensive part of operations (in the range of 45 to 60+% in the Global North) (Alcorn & Kockelman, 2020; American Public Transit Association., 2020; Litman, 2024). Ultimately, with advances in technology, cost optimisation of public transport service provision will inherently involve diminishing and eventually eliminating driver costs through automation. Some experts contend that today's fixed-route rubber-tired public transport systems will transform into a network of autonomous vehicles facilitating dynamic ride-sharing (DRS) with strong cost and service-level benefits (Brownell & Kornhauser, 2014).

Based on this, it is assumed that total automation would result in the elimination of labour costs in this sector, estimated at 45% of total operational costs.

Energy savings

CCAM deployment in passenger transport has the potential to deliver important energy savings, particularly through optimised driving patterns, reduced congestion, and improved vehicle efficiency. Hoogeven et al. (2021) estimate that the total energy and fuel savings of automation range between 0% and 40%. Public transport systems, especially those deploying automated buses, may see further gains by coordinating vehicle movements and reducing idle times, supported by digital infrastructure such as 5G connectivity. These improvements not only lower emissions but also contribute to broader sustainability and cost-efficiency goals across the transport sector.

Vehicle automation and connectivity can lead to fuel savings, primarily through eco-driving and powertrain optimization, especially in hybrids, but may also increase fuel use if not efficiency-focused. Combined, these technologies can improve internal combustion engine vehicles fuel efficiency by up to 9% in urban driving and up to 20% for plug-in hybrid electric vehicles over mixed cycles. At the system level, full deployment of autonomous vehicles could reduce total energy use by 40% or increase it by 70%, depending on changes in travel behaviour, congestion, vehicle design, and electrification, highlighting the need for strong policy oversight (The National Academies of Sciences, Engineering and Medicine, 2021).

Based on this literature, energy cost savings from automation are assumed to be at the midway point of the range set by Hooegeven et al. (2021), that is 20%.

Table 16: Summary of passenger transportation assumptions

Category	Aspect	Estimates
Investment Costs	Total incremental cost of automation (L4/5, no base vehicle)	USD 92,000 per unit. Leads to a 90.9% increase in total vehicle costs from USD 75 000 to USD 167 000
	Public Transport Automation Cost relative to baseline diesel bus	40.4%
Operational Costs	Driver Cost Share in Public Transport	45% of total operational costs
Energy Savings	Total energy and fuel savings	20% relative to non-automated alternatives

Source: Hoogeven et al. (2021); Kelkar et al. (2024); Luman (2020); Alcorn and Kockelman (2020).

Common assumptions

Sector splits

For the second and third use cases (road freight and passenger transportation), a common set of underlying assumptions needs to be established, principally relating to the composition of vehicle fleets.

A key assumption concerns the proportion of freight to passenger vehicles within the land transport and transport via pipelines sector, categorised under NACE code H49. To inform this, turnover data by mode of transportation was used (European Commission, 2024; Eurostat, 2025a). It provides mode-specific turnover figures for each EU Member State, enabling the derivation of national shares for freight and passenger transport activity.

Another important assumption relates to the breakdown of freight vehicle types, given that the adoption of CCAM technologies is expected to vary across subsegments, as discussed previously. To support this, data was gathered on the modal split within the broader freight sector covering road, rail, inland waterways, and other modes, alongside statistics on road freight transport segmented by distance class and transport type. This information allows for a differentiation between last-mile delivery vehicles and those used for medium- and long-haul operations across the Member States.

The table below presents the data sources underpinning these assumptions.

Table 17: Data sources of common assumptions

Data	Description
Freight vehicles by distance class (TKM)	<50 km, 50-149 km,150-299 km, 300-499 km, 500-999 km, 1 000-1 999 km, 2 000-5 999 km, > 6 000 km
Modal split of inland passenger transport	Total, Passenger cars, Trains, Motor coaches, buses and trolley buses
Modal split of inland freight transport	Total, Railways, Road, Inland waterways
Turnover by mode of transport	Road (Freight), Road (Passenger), Railways, Pipelines, Inland Water Transport, Sea Transport. Air Tramsport.

Warehousing, Postal And Courier

Source: European Commission (2024); Eurostat (2025a, 2025b, 2025c).

Infrastructure

To enable the effective deployment of CCAM, a range of critical infrastructure investments is required. Key among these are the development of 5G and vehicle-to-everything (V2X) communication networks, which are essential for ensuring low-latency, reliable connectivity between vehicles and the surrounding infrastructure. The installation of roadside units (RSUs) will support vehicle-to-infrastructure (V2I) interactions, while the deployment of intelligent traffic signals and advanced sensor systems will contribute to enhanced real-time traffic management.

Moreover, edge computing capabilities and cloud-based platforms will be necessary to process large volumes of mobility data securely and efficiently. Robust cybersecurity frameworks must also be embedded to mitigate risks associated with vulnerabilities in connected systems.

That said, investment requirements in infrastructure are assumed to be relatively modest in comparison to those associated with vehicle upgrades (Asselin-Miller et al., 2016). Furthermore, given the considerable variation in infrastructure needs across countries and the limited availability of consistent data on these requirements, infrastructure investments have not been explicitly modelled in this analysis.

Country adopter groups

Based on ongoing piloting, deployment, research, and development activities across the EU, Member States can be grouped into three broad categories of CCAM adoption maturity. Early adopters such as Germany, France, the Netherlands, Belgium, Sweden, and Finland are leading the way, supported by extensive public investment, favourable regulatory environments, and advanced urban mobility pilots, particularly in the realm of automated public transport. Mid adopters, including countries like Spain, Denmark, and Italy, demonstrate growing engagement through emerging initiatives and increasing interest in automation, though deployment re-mains more limited in scale. Late adopters, predominantly in Eastern and Southeast-ern Europe, are expected to show minimal adoption, constrained by weaker institutional support, poor public perception, regulatory frameworks, and limited digital infrastructure.

Table 18: Country adopter groups

Adoption stage	Member States	Supporting evidence
Early adopters	Germany, France, Netherlands, Sweden, Finland, Belgium	Advanced CCAM testbeds and pilot deployments, especially in public automated shuttles and urban mobility corridors; automation in last-mile delivery; strong public investment and regulatory support.
Mid adopters	Spain, Italy, Denmark, Austria, Portugal	Expanding CCAM initiatives with some public-private partnerships; automation in select robotic warehousing processes, moderate regulatory readiness and selective urban trials underway.
Late adopters	Greece, Hungary, Poland, Romania, Bulgaria	Few to no operational pilots; limited digital infrastructure and institutional investment; regulatory frameworks remain underdeveloped.

Source: ERTRAC (2022) and Koelman et al.(2023).

To differentiate between early, mid, and late adopters, adoption growth rates for CCAM technologies are adjusted to reflect each group's level of uptake. Early adopters are assumed to experience slightly higher growth, reflecting more favourable conditions for deployment. In contrast, late adopters face marginally lower growth rates due to less developed enabling conditions. Mid adopters retain the baseline growth rate, with no adjustment applied. The corresponding adjustment factors are presented in the table below.

Table 19: Adopter group growth adjustments

Adopter group	Growth adjustment coefficient
Early adopters	+5%
Mid adopters	0%
Late adopters	-5%

Summary and next steps

This deliverable aimed to establish the assumptions used for the modelling of CCAM in the use cases laid out in WP3C. The assumptions will be used for the modelling employment results in the next deliverable.

Table 20 summarises assumptions across the main categories discussed: adoption rates, investment costs, cost savings, and fuel savings.

Table 20: Adoption rates summary

Use case	Year	Low uptake	Medium uptake	High uptake
Warehousing	2024	25%	25%	25%
Warehousing	2030	30.65%	37%	43.93%
Warehousing	2040	43.04%	56.25%	100%
Warehousing	2050	60.44%	75%	100%
L1-L3 road freight	2025	50.32%	51.46%	53.21%
L1-L3 road freight	2030	56.27%	58.85%	62.93%
L1-L3 road freight	2040	70.37%	76.95%	88.00%
L1-L3 road freight	2050	88.00%	94.16%	85.25%
L4/L5 road freight	2025	0.25%	0.25%	0.25%
L4/L5 road freight	2030	0.42%	0.47%	0.57%
L4/L5 road freight	2040	1.17%	1.66%	2.89%
L4/L5 road freight	2050	3.26%	5.84%	14.75%
Last mile delivery	2035	1%	1%	1%
Last mile delivery	2040	1.20%	1.29%	1.37%
Last mile delivery	2050	1.73%	2.14%	2.57%
Public transportation	2027	1%	1%	1%
Public transportation	2030	1.29%	1.34%	1.41%
Public transportation	2040	3.02%	3.54%	4.37%
Public transportation	2050	7.07%	9.35%	13.57%
Private transportation	2027	0.50%	0.50%	0.50%
Private transportation	2030	0.66%	0.69%	0.72%
Private transportation	2040	1.66%	1.97%	2.47%
Private transportation	2050	4.17%	5.65%	8%

Table 21: Investment cost summary

Use case	Type	Value
Warehousing	Cost of automating the average warehouse	EUR 10 000 000
Warehousing	Additional cost of automating the average warehouse relative to baseline	62.26%
Road freight / Public transport	Total additional automation cost per vehicle	EUR 100 000
Road freight	Total additional automation cost per vehicle relative to baseline	90.9%
Road freight / Public transport	Share of hardware in automation cost	15%
Road freight / Public transport	Share of software in automation cost	85%
Road freight / Public transport	Profile of incremental automation costs	7.69% / 21.79% / 26.5% / 25.21% / 18.8%
Public transport	Additional cost of automation relative to the baseline	40.4%
Private transport	Estimated vehicle price	USD 167 000
Private transport	Automation cost (not including base vehicle)	USD 92 000
Private transport	Additional automation cost relative to baseline	55.09%
Last mile delivery	Estimated cost of AGV delivery vehicle	EUR 30 000
Last mile delivery	Additional automation cost relative to baseline	-6.07%

Table 22: Cost savings summary

Use case	Savings type	Value
Warehousing	Productivity gains from automation	45%
Warehousing	Total labour cost after automation	-65%
Road freight	Total labour cost at L3	-10%
Road freight	Total labour cost at L4	-79%
Road freight	Total labour cost at L5	-90%
Road freight	Total insurance at L4	-5%
Road freight	Total insurance at L5	-5%
Road freight	TCO savings at L4 (>1500 miles)	-42%
Road freight	TCO savings at L4 (≤250 miles)	-13%
Road freight	TCO savings at L4 (≤100 miles)	>0%
Road freight	Labour cost share in TCO	35%
Road freight / Last mile delivery	Fuel costs	-10%
Passenger transportation	Total energy and fuel cost	-20%
Public transportation	Labour cost share in TCO	45%

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