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D4.7 Social Impact Assessment

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CCAM-ERAS	101147129	CCAM Employment Realisation through Acquisition of Skills	4.7	Social Impact Assessment

AUTHORS

Christos Gkartzonikas	MaaSLab
Konstantinos Kamargiannis	MaaSLab

REVIEWERS

Jayant Sangwan	CORTE
Gunnar Lamvik	SINTEF

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Abbreviations

Abbreviation	**Definition**
CCAM	Cooperative, Connected and Automated Mobility
WP	Work Package
CCAM-ERAS	CCAM Employment Realisation through Acquisition of Skills
CO_2	Carbon dioxide
GDP	Gross Domestic Product
MAE	Mean Absolute Error
PIs	Perception Index
PPS	Purchasing Power Standard
R^2	Coefficient of determination
RMSE	Root Mean Square Error
tCO_2e	Tonnes of carbon dioxide equivalent

Executive summary

Cooperative, Connected and Automated Mobility (CCAM) is expected to affect society well beyond the operational performance of transport systems. Its progressive deployment may influence how different population groups travel, access essential services and participate in employment and education. It may also transform transport-related occupations, skills requirements, affordability, safety, well-being and the geographical distribution of mobility opportunities. These effects are not predetermined and will depend on the rate of technological penetration and the conditions under which CCAM services are introduced. Deliverable D4.7, "Social Impact Assessment", presents the development and application of a model for assessing and forecasting selected social effects associated with alternative CCAM deployment pathways. The deliverable primarily reports the work undertaken under Task 4.C.3, "Forecasting and extrapolating social effects". It builds upon Deliverable D4.6, which combined desk-based research, stakeholder interviews and a population survey conducted in the Netherlands, Belgium, Norway, Germany and Cyprus. The survey collected 1,083 responses and examined travel behaviour, technological confidence, willingness to use different CCAM services and expectations regarding accessibility, affordability, employment, skills, safety and well-being.

The social impact assessment combines statistical analysis, contextual forecasting and system dynamics modelling. It examines self-driving taxis, private automated cars, automated public buses, automated on-demand shuttles and automated delivery applications. The model represents the relationships among CCAM availability, public acceptance, service adoption and a set of social-impact domains. These include adoption and participation, accessibility and affordability, employment and skills, inclusion and equity, well-being and safety, and longer-term spatial effects. Population heterogeneity is represented through characteristics such as age, gender, education, employment status, residential context, technological confidence, driving-licence possession and vehicle ownership. Low-, reference- and high-penetration scenarios are used to examine possible developments over short-, medium- and long-term horizons, represented principally by 2030, 2040 and 2050. The findings indicate that greater CCAM penetration increases the potential scale of both beneficial and adverse effects. Automated taxis, buses and on-demand shuttles could improve mobility for non-drivers, older people and populations with limited access to conventional transport. Nevertheless, technological availability does not automatically produce social accessibility. Service cost, geographical coverage, accessible vehicle and interface design, strongly influence whether different groups can use and benefit from these services.

The results also show that adoption is likely to occur unevenly. Technologically confident users and populations located in the initial deployment areas are expected to adopt CCAM earlier. Without inclusive deployment conditions, financial, digital, physical and territorial barriers may remain even as overall penetration increases. Employment effects are expected to involve a combination of task displacement, occupational transformation and the creation of new technical and supervisory roles. Higher penetration also increases demand for digital, technical and interdisciplinary skills, while timely reskilling can reduce the duration of workforce disruption. Potential reductions in travel-related stress, accidents and fatalities become more visible as automated mobility accounts for a larger share of travel. Longer-term effects may include changes in residential location and increased travel distances, especially under scenarios dominated by private automated vehicles. The forecasts should be interpreted as conditional projections rather than precise predictions. They depend on stated preferences, stakeholder expectations, contextual data and explicit assumptions concerning future technological development. The next stage, undertaken under Task 4.C.4 and reported in D4.8, will involve the structured review of the model, its assumptions and its forecasting results by relevant experts and stakeholders.

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1 Introduction

1.1 Background

The progressive development of Cooperative, Connected and Automated Mobility (CCAM) is expected to generate changes extending well beyond the operation and performance of transport systems. As automated passenger and freight mobility solutions move towards higher levels of technological maturity and market penetration, they may influence how people travel, access essential services, participate in employment and education, and interact with the wider mobility system. Further, CCAM deployment may affect employment structures, skills requirements, transport affordability and the distribution of mobility opportunities among different population groups. The scale and direction of these effects are not predetermined. CCAM technologies may improve accessibility, safety and convenience, particularly for people who currently experience restrictions in their mobility. These groups may include older people, people with special mobility needs, individuals without access to a private vehicle and people living in areas with limited conventional public transport provision. Nevertheless, the realization of these benefits depends on several conditions, including service availability, pricing, technological accessibility, public acceptance, digital capabilities and the geographical distribution of CCAM services. If these conditions are not sufficiently considered, the deployment of CCAM could reinforce existing transport inequalities or introduce new forms of exclusion.

Similar uncertainty surrounds the effects of CCAM on employment and skills. Increasing automation may reduce the demand for certain conventional driving and operational tasks, while simultaneously creating or expanding occupations associated with data analysis, artificial intelligence, cybersecurity, systems supervision, fleet management and digital mobility services. The overall social effect will depend not only on the number of jobs affected but also on the capacity of workers, employers and educational institutions to respond to changing skills requirements. The timing of deployment is particularly important because employment displacement and the creation of new opportunities may occur at different rates.

These interdependencies make it difficult to assess the social consequences of CCAM through isolated indicators or static comparisons. Changes in public acceptance may influence the rate of adoption, while adoption may affect operating costs, service availability and the willingness of additional users to participate. Similarly, improvements in accessibility may increase the number of trips undertaken by previously underserved groups, whereas lower perceived safety or limited technological confidence may restrict adoption. The effects may also differ considerably across population groups, geographical contexts, CCAM use cases and levels of automation.

A forward-looking assessment therefore requires a modelling framework capable of representing these relationships over time. Such a framework should combine evidence about stakeholder expectations and population preferences with assumptions concerning technological development and CCAM market penetration. It should also allow alternative deployment scenarios to be explored rather than presenting a single deterministic prediction of the future. Within this context, Work Package (WP) 4C of the CCAM-ERAS project addresses the economic and societal effects associated with the development and deployment of CCAM technologies and services. The work progresses from the identification and mapping of potential social effects to their systematic modelling and forecasting. This approach supports a more comprehensive understanding of how different CCAM development pathways could influence citizens, workers, organizations and communities over short-, medium- and long-term horizons.

1.2 Objectives of Deliverable 4.7

Deliverable D4.7 “Social Impact Assessment”, presents the development and application of a model for assessing and forecasting selected social effects associated with CCAM deployment. The deliverable builds upon the evidence collected through stakeholder engagement and the population survey undertaken within CCAM-ERAS and translates this evidence into a structured modelling framework.

The principal objective is to move from the identification and descriptive mapping of potential impacts towards an analytical representation of how these impacts may evolve under alternative CCAM deployment conditions. The model considers the interrelationships between technological development, market penetration, public acceptance and a selected set of societal outcomes. Particular attention is given to the possibility that the effects of CCAM will not be distributed uniformly across the population.

More specifically, D4.7 aims to:

- establish the conceptual structure of the CCAM-ERAS social impact assessment model;
- define the social-impact domains, variables and causal relationships represented within the model;
- demonstrate how evidence obtained from stakeholders and population groups informs the formulation of the model;
- describe the statistical, forecasting and system dynamics methods applied;
- define alternative scenarios reflecting different rates of CCAM penetration and different levels or forms of automation;
- forecast selected social effects over short-, medium- and long-term horizons;
- compare outcomes across CCAM use cases, scenarios and relevant population characteristics; and
- identify the principal assumptions, uncertainties and limitations associated with the forecasts.

The model is intended to support the exploration of possible future developments rather than to predict one definitive trajectory for CCAM. Its outputs should consequently be interpreted as conditional projections: they illustrate how selected social indicators could evolve if the assumptions associated with a given scenario were realized. This distinction is particularly important because the current empirical evidence concerning large-scale CCAM deployment remains limited and because the pace of technological, regulatory and market development is uncertain.

The modelling work takes as one of its methodological starting points the system dynamics approaches developed through the MOVE2CCAM Impact Assessment Modelling Tool. Within CCAM-ERAS, the relevant modelling components are reconsidered and enhanced to provide greater emphasis on social variables, population-group differences and evidence emerging from the project’s engagement activities. The purpose is therefore not to reproduce the MOVE2CCAM tool or its complete multidimensional assessment framework, but to advance the underlying modelling approach in response to the specific objectives and evidence base of CCAM-ERAS.

Through this approach, D4.7 provides a structured foundation for understanding the possible scale, timing and distribution of CCAM-related social effects. The findings are intended to inform subsequent project activities and contribute to the development of policies and implementation strategies that recognize both the potential benefits of automated mobility and the associated risks of exclusion, uneven access and workforce disruption.

1.3 Relationship with Previous CCAM-ERAS Deliverables

D4.7 forms part of WP4C and primarily reports the activities undertaken under Task 4.C.3, “Forecasting and extrapolating social effects”. Its immediate empirical foundation is Deliverable D4.6, “Stakeholders’ and Population Groups Impact Analysis and Mapping”, which documented the social effects identified through desk-based research, stakeholder interviews and the CCAM-ERAS population survey.

D4.6 examined CCAM from two complementary perspectives. The stakeholder analysis captured the expectations and concerns of higher and vocational education institutions, industry representatives, road transport operators and representative organisations. The population-group analysis examined citizens’ travel behaviour, technological confidence, willingness to use different CCAM services and perceptions of possible effects on accessibility, employment, safety, travel costs and well-being. D4.7 uses these findings to identify relevant model variables, define relationships between them and inform assumptions concerning the direction and relative importance of selected social effects.

The modelling work is also informed by the wider CCAM-ERAS analysis of anticipated CCAM developments and use cases. Where relevant, outputs from other WP4 activities provide contextual information concerning employment and skills developments. These wider connections support consistency across the project but are not the primary analytical focus of D4.7. The relationship between D4.6 and D4.7 can therefore be understood as a progression from evidence collection and impact mapping to model formulation and forecasting. D4.6 identifies the social effects that stakeholders and citizens expect or consider important, whereas D4.7 examines how selected effects could develop over time under different CCAM deployment scenarios. The forecasts are supported by explicit assumptions and should be interpreted in conjunction with the empirical and methodological limitations documented in the deliverable.

The assessment developed in D4.7 will subsequently provide the basis for Task 4.C.4 and Deliverable D4.8. That next stage will focus on engaging relevant industry actors, experts and stakeholder representatives in reviewing the model structure, assumptions and projected social effects. The validation process and any resulting model refinements will therefore be documented separately in D4.8 and are not part of the present deliverable.

1.4 Structure of the Deliverable 4.7

Following this introductory section, the deliverable presents the evidence base and analytical scope underpinning the social impact assessment. It explains how the findings obtained from stakeholders and population groups were translated into model requirements and describes the CCAM services, social-impact dimensions and contextual factors considered in the analysis.

The subsequent part of the deliverable introduces the social impact assessment model. It defines the model boundaries, principal variables and causal relationships and describes the combination of statistical analysis, forecasting techniques and system dynamics modelling used to examine changes over time. It also explains how population heterogeneity and different CCAM penetration assumptions are represented.

The deliverable then describes the operationalization of the modelling approach, including the enhancement of relevant model components previously applied in MOVE2CCAM. This includes the introduction of additional social input variables, the revision of selected equations and the adaptation of model relationships to reflect evidence generated within CCAM-ERAS.

The forecasting section presents the results obtained under the alternative deployment scenarios. The findings are organized around the principal social-impact domains and include comparisons across time horizons, use cases and relevant population characteristics. Particular attention is paid to the conditions under which CCAM may generate improvements in accessibility, inclusion and well-being, as well as the circumstances in which adverse or unevenly distributed effects may emerge. Finally, the deliverable summarizes the principal findings, discusses the limitations of the assessment and identifies the next steps towards the validation of the model and its forecasts under Task 4.C.4 and D4.8.

2 Evidence base and analytical scope

2.1 Evidence Transferred from the Stakeholder and Population-group Impact Analysis

The development of the social impact assessment model builds directly upon the work undertaken in Deliverable D4.6, “Stakeholders’ and Population Groups Impact Analysis and Mapping”. D4.6 established the empirical foundation for understanding how different actors anticipate that Cooperative, Connected and Automated Mobility technologies and services may affect society. Rather than approaching CCAM exclusively as a technological development, the analysis examined how its deployment could influence accessibility, employment, skills, affordability, social inclusion, safety, well-being and the organisation of passenger and freight transport services.

D4.6 combined three principal sources of evidence. First, desk-based research was used to identify the social and socio-economic effects most frequently associated with automated mobility in the existing academic and policy literature. Second, interviews with stakeholders from several sectors provided qualitative insights into the mechanisms through which these effects may emerge and the conditions under which they may become positive or negative. Third, a population survey conducted across five European countries captured citizens’ willingness to use selected CCAM services and their expectations regarding the broader effects of automated mobility.

These three sources serve different but complementary purposes in the modelling process. The desk-based research provides the conceptual foundation and supports the identification of relevant relationships. The stakeholder interviews contribute practical and sector-specific knowledge about technological deployment, employment transformation, service provision and institutional preparedness. The population survey provides structured quantitative evidence on acceptance, expected use and perceived impacts across different national and demographic contexts. Together, they enable the social impact assessment model to be grounded in both existing knowledge and evidence generated specifically within CCAM-ERAS.

2.1.1 Evidence from the Desk-based Research

The desk-based research undertaken in D4.6 demonstrated that the social effects of CCAM are likely to be multidimensional and, in several cases, interdependent. Potential improvements in one area may be accompanied by adverse effects in another. For example, increased automation could reduce certain operating costs and improve service efficiency, but it may also displace workers performing conventional driving or operational tasks. Similarly, automated mobility could improve independent travel for older people and people with special mobility needs, but only if vehicles, booking systems and associated infrastructure are accessible and affordable.

The literature examined in D4.6 associated CCAM deployment with potential improvements in road safety, transport efficiency, accessibility and travel convenience. Automated vehicles may reduce some forms of human error, provide new mobility options for people who cannot drive and allow travel time to be used for other activities. Shared or on-demand automated services may also extend the reach of public and collective transport, particularly where conventional fixed-route services are difficult or costly to provide.

However, the desk-based analysis also identified important risks. These include increased vehicle travel resulting from lower perceived travel costs, additional empty-vehicle movements, pressure on existing public transport services, increased urban sprawl and unequal access to new mobility services. Early CCAM services may be concentrated in technologically advanced, commercially attractive or densely populated areas. Consequently, rural communities, low-demand areas and groups with limited digital access may benefit later or to a lesser extent.

Employment was identified as another central area of uncertainty. Automation is expected to modify the demand for conventional driving occupations and supporting services. The effects may extend beyond drivers to vehicle maintenance, insurance, logistics, customer service and transport administration. At the same time, new occupational profiles may emerge in areas such as fleet supervision, systems engineering, cybersecurity, software development, remote operations and mobility data management. The net employment effect will depend on the rate of deployment, the sectors affected, the extent to which existing roles are transformed rather than eliminated and the availability of appropriate reskilling pathways.

The evidence reviewed in D4.6 therefore supports an assessment framework that can represent both beneficial and adverse outcomes. It also highlights the need to move beyond average effects and consider their distribution among population groups, sectors and geographical areas. These conclusions informed the selection of the social-impact dimensions represented in the assessment model.

2.1.2 Evidence from Stakeholder Engagement

The stakeholder component of D4.6 involved four broad categories: higher education and vocational education institutions, industry representatives, road transport operators, and representative organizations such as trade unions and sectoral alliances. The interviews explored perceptions of the socio-economic transformation associated with CCAM, including implications for business models, employment, skills, social equity, health, well-being, affordability and access to essential services. Although the stakeholder categories approached CCAM from different institutional perspectives, several common themes emerged. Stakeholders generally recognized that CCAM could produce substantial changes in transport-related occupations, service delivery and skills requirements. There was also broad agreement that the resulting effects would depend on the way in which deployment is governed and supported. Automation was not perceived as producing a uniform set of consequences; instead, its effects were understood as being conditional on factors such as the pace of deployment, organizational readiness, service design, public investment and the availability of training.

Higher education institutions and vocational education institutions primarily considered CCAM through the lenses of skills development, knowledge creation and workforce preparation. These stakeholders expected increasing demand for interdisciplinary competencies combining transport engineering, digital systems, artificial intelligence, data analysis, cybersecurity and regulatory knowledge. They also identified a need for non-technical capabilities, including communication, ethical reasoning, service design and the capacity to work across institutional and disciplinary boundaries. At the same time, education and training providers reported challenges in responding quickly to technological change. The process of revising curricula, approving new programs and establishing new training infrastructure may progress more slowly than technological development. This creates a potential time lag between the emergence of labor-market needs and the availability of workers with appropriate qualifications. The stakeholder evidence therefore suggests that the social impact assessment should not treat workforce adaptation as an instantaneous response. Changes in skills supply are more appropriately represented as gradual processes influenced by institutional capacity, investment and collaboration between industry and education.

Education stakeholders also emphasized the importance of ensuring that new CCAM-related employment opportunities are accessible to a broad range of learners. If future jobs require highly specialized qualifications that are accessible only to a limited part of the population, the benefits of employment creation may be unevenly distributed. The transition could consequently disadvantage workers whose previous occupations are affected by automation, but who face barriers to participating in new training. From a modelling perspective, the availability and accessibility of reskilling opportunities can therefore influence the relationship between technological penetration, job displacement and longer-term employment outcomes.

Industry stakeholders placed greater emphasis on innovation, operational efficiency and the development of new products and services. They associate CCAM with opportunities for business-model development in areas such as automated passenger mobility, shared services, logistics, e-commerce and data-enabled mobility management. CCAM could reduce certain operating costs, increase service availability and enable new combinations of passenger and freight transport services. Industry stakeholders nevertheless acknowledged that the early stages of deployment may require substantial investment. Vehicles, digital infrastructure, connectivity, cybersecurity, mapping, maintenance and remote supervision all contribute to the cost of implementation. The affordability of CCAM services may therefore change over time as the technology matures and operations expand. This introduces a potentially important feedback relationship: increased deployment may enable economies of scale and reduce service costs, while lower costs may subsequently increase public adoption. Conversely, high initial prices could limit uptake, delay scaling and concentrate early access among individuals or organizations with greater financial resources.

Road transport operators approached the transition from a more operational perspective. Their responses reflected concerns about service continuity, workforce impacts, capital requirements and the practical integration of automated vehicles into mixed transport environments. Operators recognized possible improvements in efficiency and service coverage but were cautious about the speed with which such benefits might be achieved. The transition towards highly automated operations may proceed through intermediate phases in which human drivers, safety operators, remote supervisors and automated systems coexist. During these phases, some jobs may change in content rather than disappear. Conventional driving responsibilities could gradually be combined with customer assistance, vehicle monitoring, system supervision or emergency-response functions. The model should therefore avoid assuming that automation produces an immediate one-to-one replacement of human labor. The relationship between technological penetration and employment is likely to involve delays, transitional roles and differences among passenger transport, freight transport and logistics.

Transport operators also raised affordability concerns. Although automation may eventually reduce some labor or operating costs, the initial investment required for vehicles and infrastructure may increase the cost-of-service provision. The effect on users will depend on whether these costs are absorbed by operators, supported through public funding or transferred to passengers and customers. As a result, technological deployment alone does not determine affordability. Governance arrangements, funding mechanisms and business models are also important. Representative organizations and trade unions placed particularly strong emphasis on the distributional consequences of the transition. These stakeholders highlighted the risk that workers in routine or lower-skilled occupations could bear a disproportionate share of adjustment costs. They consequently called for early social dialogue, transparent workforce planning and accessible retraining opportunities. From their perspective, a socially sustainable transition requires mechanisms that allow workers and their representatives to participate in decisions concerning the introduction of automated technologies.

Representative organizations also emphasized that accessibility and affordability should be embedded within the design of CCAM services rather than addressed only after deployment. Market-led introduction may prioritize locations and users that offer the strongest commercial returns. Without complementary public policies, this could leave low-demand areas or disadvantaged populations with limited access. Targeted subsidies, service obligations, public–private partnerships and accessible-design requirements were identified as possible mechanisms for influencing the distribution of benefits. Across the four stakeholder categories, health and well-being effects were discussed in relation to both users and workers. For users, CCAM may reduce the stress associated with driving, navigation, parking and unreliable transport. It may also support greater independence and social participation. For workers, automation could remove certain physically demanding or stressful tasks. However, it could also introduce new sources of stress associated with employment insecurity, continuous technological adaptation, remote monitoring and changing responsibilities.

This evidence supports the treatment of well-being as a multidimensional outcome. Reduced travel stress for users should not automatically be interpreted as improved well-being for every group affected by CCAM. Different effects may occur simultaneously, and the overall outcome depends on whose experience is being assessed.

2.1.3 Evidence from the Population Survey

The population-group analysis in D4.6 was based on an online survey conducted between March and April 2025 in the Netherlands, Belgium, Norway, Germany and Cyprus. A total of 1,083 valid responses were collected: 230 from the Netherlands, 217 from Belgium, 203 from Norway, 366 from Germany and 67 from Cyprus. Age and gender quotas were applied to support diversity within the national samples. The questionnaire consisted of four principal components. The first collected information on respondent characteristics, including age, gender, education, place of residence, employment status, technological confidence and self-perceived position in the innovation-adoption process. The second examined existing travel behavior, including driving-license possession, household vehicle ownership, use of different transport modes and the frequency of deliveries. The third presented several passenger and freight CCAM use cases and asked respondents about their willingness to use them. The fourth asked respondents to assess the potential effects of self-driving vehicles across a range of mobility, social, economic and safety indicators.

The survey examined willingness to use self-driving taxis for work and non-work journeys, willingness to purchase or lease a self-driving private car, willingness to use a self-driving public bus and willingness to use a private automated delivery or pick-up robot. Respondents were asked to consider conditions under which the cost and travel time of the automated service were comparable with those of the corresponding conventional alternative. This approach made it possible to examine acceptance while holding two important service attributes relatively constant. Respondents were also asked when they expected several CCAM services to be implemented in their cities. The services included self-driving taxis, private cars, public buses, on-demand shuttle buses and private delivery or pick-up robots. The response options covered five-year intervals from 2030 to 2050 and included the possibility that a service might never be implemented. These responses provide information about public expectations rather than technical deployment forecasts. Nevertheless, they are valuable for understanding how citizens perceive the maturity and proximity of different CCAM technologies.

For selected use cases, the survey also examined possible behavioral responses. These included the proportion of conventional journeys or deliveries that respondents might substitute with automated services, possible changes in the number of trips or deliveries and possible implications for residential location. These questions provide a bridge between general acceptance and potential system-level effects. A person who expresses willingness to use an automated service may substitute existing journeys, generate additional journeys or change other aspects of their behavior. These responses can therefore inform the relationships between adoption, travel activity and longer-term spatial effects. The final part of the survey examined expectations regarding the wider effects of self-driving vehicles. Respondents assessed possible changes in:

- the number of trips made by citizens;
- the number of vehicles using the transport network;
- travel time;
- the cost of passenger journeys;
- delivery costs;
- transport-sector emissions;
- economic growth and investment;
- employment opportunities and job losses;
- requirements for new skills;
- accessibility for the general population;
- accessibility for people with special mobility needs;
- accessibility for older people;
- accessibility for families with children;
- travel-related stress;
- traffic accidents; and
- traffic fatalities.

The response scale ranged from a significant reduction to a significant increase or improvement. These responses provide a broad indication of the direction and relative strength of public expectations. However, they represent perceived future impacts rather than observed causal relationships. For this reason, they are used cautiously within the model. They support the identification and relative calibration of relationships but are not automatically interpreted as direct forecasts of percentage changes. The comparative analysis in D4.6 identified a general pattern of cautious optimism. Respondents frequently recognized the potential of automated mobility to improve accessibility and safety, while also anticipating employment disruption and new skills requirements. At the same time, acceptance was not uniform across countries or population characteristics. Technological confidence, familiarity with innovation, existing travel behavior and residential context appeared relevant to the way respondents assessed CCAM services.

The results also indicated that attitudes could differ across use cases. A respondent may be willing to use a self-driving public bus but unwilling to purchase a private automated car or may accept an automated delivery service while remaining hesitant about automated passenger transport. This confirms that CCAM acceptance should not be represented by a single general variable. Adoption is service-specific and may also differ according to trip purpose. Differences among age groups, residential contexts and levels of technological confidence further demonstrate the importance of population heterogeneity. Younger and technologically confident respondents generally appeared more receptive to emerging mobility technologies, whereas older or less technologically confident respondents tended to display greater caution. These relationships should not be interpreted deterministically: age alone does not determine acceptance, and older populations are not homogeneous. Nevertheless, the results suggest that digital confidence, familiarity and perceived ease of use can influence adoption.

Residential context is also relevant. People living in city centers, other urban areas, suburbs and villages may experience different levels of conventional transport accessibility and may therefore evaluate the potential usefulness of CCAM differently. An automated service that offers marginal convenience in a well-served urban area could provide a more substantial accessibility improvement in a location with limited conventional transport. Conversely, lower-density areas may face slower deployment because of infrastructure or commercial constraints. The survey provides direct information on several respondent characteristics but does not support direct estimation for every vulnerable population addressed conceptually in WP4C. In particular, perceived accessibility for older people and people with special mobility needs was measured, but the survey evidence does not necessarily identify respondents as belonging to each of these groups. The model therefore distinguishes between observed differences based on the respondent characteristics collected and perceived effects concerning groups discussed more generally. Evidence from stakeholder interviews and desk-based research complements the latter.

The different national sample sizes must also be considered when using the survey findings. The comparatively small Cyprus sample, for example, produces greater statistical uncertainty than the larger German sample. Accordingly, the model should avoid interpreting small differences in raw national percentages as definitive country effects. National context can be represented where supported by the data, but comparisons should recognize differences in sample precision and the exploratory nature of some findings.

2.1.4 Convergence and Divergence between Stakeholders and Citizens

The combination of stakeholder and population evidence is important because the two groups observe CCAM from different positions. Stakeholders tend to assess deployment through sectoral, operational and institutional considerations. Citizens tend to evaluate CCAM in relation to personal mobility, convenience, safety, affordability and confidence in automated services. Neither perspective is sufficient on its own. Several areas of convergence were identified. Both stakeholders and citizens recognised the potential for CCAM to improve accessibility. Stakeholders frequently discussed independent mobility for older people, people with disabilities and residents of underserved areas. Citizens similarly anticipated improvements in accessibility for the general population and for groups with specific mobility needs. This convergence supports the inclusion of accessibility as a central social-impact domain.

Employment and skills represent another area of convergence. Stakeholders expected changes in occupational profiles and a growing need for digital and technical competencies. Citizens also anticipated job losses and increasing skills requirements. Although the two evidence streams cannot directly determine the future number of jobs created or displaced, they consistently identify workforce transformation as an important social consequence. Safety was also viewed as a potential benefit, particularly if automation reduces accidents associated with human error. Nevertheless, both the literature and engagement findings indicate that perceived safety is also a condition for adoption. Safety therefore has a dual role: it is a potential outcome of CCAM deployment and an input influencing public acceptance.

Affordability emerged as a conditional factor across both evidence streams. Stakeholders noted that operating costs could decrease as the technology matures but that the early stages of implementation may be expensive. Citizens' responses were elicited under assumptions of comparable cost and travel time, implicitly demonstrating the importance of these attributes for acceptance. The model must therefore distinguish between technological availability and effective accessibility. A service may exist without being affordable to the groups that could benefit from it most. Some differences between stakeholders and citizens are equally informative. Industry stakeholders often focused on longer-term efficiency, scaling and business-model opportunities, while citizens evaluated services under more immediate and personal conditions. Transport operators and representative organisations placed stronger emphasis on transition costs and workforce impacts. These differences do not necessarily represent contradictions. Instead, they indicate that the timing, distribution and perception of impacts may vary.

D4.7 uses this combined evidence to construct a model that is explicitly conditional and scenario based. Positive outcomes are not assumed to result automatically from higher levels of automation. They emerge under combinations of service availability, affordability, public acceptance, accessible design, skills preparation and supportive deployment conditions. Similarly, negative outcomes are not treated as unavoidable. Their magnitude may be reduced through alternative implementation pathways and supporting measures.

Table 1 presents an overview of the perspectives' comparison of stakeholder and citizen including implications for the social impact assessment model.

Table 1 Comparison of stakeholder and citizen perspectives and implications for the social impact assessment model

Social-impact dimension	Stakeholder perspective	Citizen perspective	Convergence or divergence	Implication for the model
Accessibility	Stakeholders expect CCAM to improve mobility for older people, people with disabilities, non-drivers and residents of underserved areas. However, they stress that these benefits depend on inclusive service design, geographical coverage and supportive policy.	Citizens generally anticipate improvements in accessibility for the general population, older people, families with children and people with special mobility needs. Some respondents nevertheless expect accessibility barriers to remain or increase.	Strong convergence regarding the potential benefit, accompanied by shared recognition that improvement is not automatic.	Accessibility is included as a central outcome, conditional on service coverage, affordability, digital accessibility and population-group characteristics.
Affordability	Industry anticipates that technological maturity and economies of scale may reduce costs over time. Operators and representative organisations are more concerned about high initial investment and the potential transfer of costs to users.	Citizens' willingness to use was generally examined under the assumption that automated and conventional services had comparable costs and travel times, confirming the importance of these attributes for acceptance.	Convergence on the importance of affordability, but different expectations regarding when cost reductions may occur.	Service cost is represented as a scenario variable influencing adoption and effective accessibility. Different assumptions are used for early and more mature deployment stages.
New employment opportunities	Industry expects new roles in software, data management, cybersecurity, systems supervision, fleet management and maintenance. Other stakeholders caution that new jobs may not be accessible to workers whose existing roles are displaced.	Citizens recognize that CCAM may create employment opportunities, but optimism about job creation is generally more restrained than concern about job losses.	Partial convergence. Both groups recognize the creation of new occupations, but citizens appear less certain that these opportunities will offset displaced jobs.	The model distinguishes among jobs displaced, jobs transformed and jobs created. Job creation and displacement are not assumed to occur at the same time or affect the same workers.
Employment displacement	Operators and representative organizations identify driving and routine operational occupations as particularly exposed. Industry expects	Citizens commonly associate CCAM with potential job losses, especially in conventional driving-related occupations.	Broad convergence regarding the risk of disruption, although stakeholders provide more detail on affected tasks and transitional roles.	Employment effects are represented as gradual and sector-dependent rather than as an immediate one-to-one replacement of workers.

	some tasks to be automated while others are transformed or newly created.			
Skills and reskilling	All stakeholder categories identify increasing demand for digital, technical and interdisciplinary competencies. Education stakeholders emphasize delays in curriculum development and training provision.	Citizens generally expect CCAM to increase requirements for new skills.	Strong convergence on the direction of the effect.	Skills availability is represented as an intermediate factor influencing whether displaced workers can transition to emerging roles. Time delays are included between the identification of skills needs and workforce adaptation.
Safety	Stakeholders identify accident reduction as a possible benefit but stress the importance of technological reliability, regulation and operation in mixed-traffic conditions.	Citizens frequently expect reductions in accidents and fatalities, while safety concerns can simultaneously reduce willingness to use automated services.	Convergence on the potential for improved safety, combined with uncertainty regarding the reliability of emerging systems.	Safety is represented both as a possible outcome of CCAM deployment and as a perception influencing adoption.
Travel-related well-being	Stakeholders expect CCAM to reduce the effort and stress associated with driving, parking and unreliable transport. They also identify possible workforce stress related to job insecurity and changing responsibilities.	Citizens generally associate CCAM with the potential to reduce travel-related stress, although reactions may differ according to trust and technological confidence.	Convergence regarding potential user benefits, while stakeholders identify additional workforce-related effects.	User well-being and workforce effects are distinguished. Reduced travel stress is not interpreted as an improvement in well-being for every affected group.
Public acceptance	Stakeholders consider awareness, demonstration activities, transparent communication and practical experience important for building trust.	Citizens display different levels of willingness to use CCAM according to use case, personal characteristics and technological confidence.	Strong convergence that acceptance develops gradually and is influenced by experience and information.	Adoption is modelled dynamically and separately for each use case. Awareness, technological confidence and perceived safety influence uptake.
Digital inclusion	Stakeholders warn that app-based or highly digital services may exclude people with limited digital capabilities unless alternative access channels are provided.	Differences in technological confidence and innovation-adoption profiles indicate that not all citizens will interact with CCAM services in the same way.	Strong convergence on the relevance of digital capabilities.	Technological confidence is included as a determinant of adoption. Inclusive and non-inclusive service-design assumptions can be examined through alternative scenarios.
Geographical coverage	Operators and representative organizations expect early services to be concentrated in areas with stronger infrastructure and higher demand.	Respondents living in urban, suburban and village contexts may assess the usefulness and accessibility of CCAM differently.	Convergence on the importance of geographical context, although stakeholders focus on deployment viability and citizens on personal usefulness.	Residential context and service coverage are used to differentiate accessibility and adoption outcomes.

Public transport relationship	Stakeholders identify opportunities for automated buses and shuttles but also a risk that commercially oriented services could compete with or weaken conventional public transport.	Citizens may view automated public transport as more accessible than privately owned CCAM, particularly when cost and travel time remain comparable with conventional services.	Partial convergence. Both recognize the potential value of collective CCAM, while stakeholders place greater emphasis on system-level consequences.	Automated public transport and privately operated CCAM services are assessed separately. Scenarios can distinguish complementary deployment from substitution of conventional public transport.
Spatial and residential effects	Stakeholders and the literature recognize that reduced travel burden may influence residential choices and contribute to spatial dispersion.	Some citizens indicate that easier or more productive travel could affect where they choose to live, although substantial change is not expected for all respondents.	General convergence on the possible direction of the effect, with considerable uncertainty regarding its magnitude.	Residential relocation and urban-sprawl effects are treated as longer-term and secondary outcomes rather than immediate consequences.
Governance and supporting measures	Stakeholders emphasize regulation, public funding, service obligations, social dialogue and inclusive design as determinants of the eventual social outcome.	Citizens primarily express expectations about service consequences rather than the institutional mechanisms required to produce them.	Difference in perspective rather than direct disagreement. Stakeholders focus on implementation mechanisms, while citizens focus on experienced outcomes.	Policy and deployment conditions are represented through scenario assumptions

2.2 Translation of the Evidence into the Analytical Scope and Model Requirements

The transition from impact mapping to model development requires the evidence assembled in D4.6 to be converted into a coherent analytical structure. This does not imply that every observation from the stakeholder interviews or every variable included in the population survey is represented as a separate component of the model. Such an approach would produce an unnecessarily complex structure with overlapping variables and limited explanatory value. Instead, the evidence is consolidated into a set of mechanisms, relationships and social outcomes that can be represented consistently across different CCAM scenarios.

The analytical scope is defined around the social effects that can plausibly be linked to the deployment and use of CCAM services over time. It includes effects experienced directly by users, such as changes in accessibility, travel costs and stress, as well as broader effects associated with employment, skills, safety and spatial behaviour. The scope also recognises that deployment occurs within a wider transport and societal context. The model therefore incorporates contextual variables and assumptions where they influence the direction or magnitude of the social effects under examination.

2.2.1 Combined Use of the Evidence Streams

The qualitative and quantitative evidence is not used interchangeably. Each source contributes to a different part of the model-development process. Stakeholder interviews are primarily used to identify causal mechanisms, implementation conditions, institutional responses and possible feedback relationships. For example, stakeholders indicated that increased automation may reduce demand for certain driving tasks but also increase demand for new technical and supervisory roles. They also indicated that the availability of reskilling can influence whether displaced workers move into emerging occupations or experience longer-term exclusion from the labour market. These relationships inform model structure even where the interviews do not provide numerical parameter values.

The population survey provides structured evidence about relative acceptance, differences across respondents, use-case preferences and perceived impacts. It supports the estimation of adoption-related relationships and the identification of population characteristics associated with greater or lower willingness to use CCAM. It also provides information on expected implementation timing and the perceived direction of broader social effects. Desk-based evidence supports the interpretation of both sources and provides a basis for identifying relationships that may not yet be observable through real-world CCAM deployments. External and contextual data can subsequently support baseline values and time-dependent trends. The modelling framework therefore combines project-generated evidence with broader empirical information while clearly distinguishing between observed data, stated expectations and scenario assumptions. A simplified representation of the evidence translation is provided below.

Table 2: Alignment for evidence component with model principal contribution

Evidence component	Principal contribution to the model
Desk-based research	Identification of established and emerging CCAM social-impact mechanisms
Stakeholder interviews	Causal relationships, implementation conditions, sectoral effects and institutional responses
Population survey	Adoption propensity, use-case differences, population heterogeneity and perceived impacts
Existing travel behavior	Baseline exposure to transport services and potential for substitution
Expected implementation timing	Public expectations concerning the temporal development of CCAM services
Contextual and regional data	Baseline conditions and external trends
CCAM deployment scenarios	Assumptions concerning automation, service availability and market penetration

2.2.2 CCAM Services Represented in the Assessment

The analytical framework covers passenger and freight applications that were considered during the CCAM-ERAS engagement activities. The population survey provided detailed evidence for self-driving taxis, self-driving private cars, self-driving public buses and private delivery or pick-up robots. It also captured expected implementation timing for self-driving on-demand shuttle services. These use cases represent distinct forms of CCAM and cannot be assumed to produce identical social effects. A self-driving private car retains the individual or household ownership model. Its effects may be associated with independent mobility, vehicle ownership, travel-time use and possible changes in residential location. If automated private vehicles reduce the perceived burden of travelling, users may become willing to make longer journeys or live further from employment and services. Such behavioral responses may increase accessibility for some households while also contributing to additional vehicle travel and spatial dispersion.

Self-driving taxis represent an on-demand service model in which access does not require vehicle ownership. They may reduce the need to own a private car and provide flexible door-to-door mobility. However, their accessibility depends on service coverage, waiting time, fare structure, booking mechanisms and vehicle design. Their effects may differ between urban areas with high demand and lower-density areas where operating costs are greater. Self-driving public buses represent the application of automation within collective transport. Potential social effects include service-frequency improvements, longer operating hours and better coverage where driver availability or labor costs currently constrain provision. Nevertheless, the benefits depend on whether operational savings are used to expand services and whether the removal or transformation of the driver's role affects passenger assistance, security and confidence.

On-demand automated shuttles combine elements of public transport and flexible mobility. They may be particularly relevant for first- and last-mile connections, peri-urban areas, campuses, industrial areas and locations where fixed-route services cannot efficiently meet dispersed demand. Their social value may arise from improved access rather than large reductions in travel time. Their effects must therefore be assessed in relation to the conventional services and population needs of the area in which they are introduced. Private delivery and pick-up robots represent a freight and logistics application with different behavioral and employment implications. They may substitute conventional delivery trips, affect the number of online orders and alter delivery costs. Their deployment may also influence employment in last-mile logistics and generate new requirements related to fleet monitoring, maintenance and digital operations.

The inclusion of multiple use cases allows the assessment to avoid treating CCAM as a single technology. The model structure retains common social-impact dimensions but allows the strength and direction of relationships to vary by service. For example, the accessibility effect of a public automated bus may be stronger for non-drivers than that of a private automated car, while the employment effects of a delivery robot may be concentrated in different occupational categories. The treatment of automation levels also requires care. The social consequences of conditional automation are not necessarily equivalent to those of highly or fully automated services. Level 3 automation may continue to require a capable human driver under certain conditions, whereas Levels 4 and 5 can enable substantially different service and ownership models. The scenarios therefore consider the degree to which automation changes the role of the human operator, the accessibility of the service to non-drivers and the potential substitution of existing employment tasks.

2.2.3 Population Groups and Heterogeneity

A central requirement of the model is the capacity to represent variation within the population. Regional or national averages may conceal substantial differences in acceptance, access and exposure to adverse effects. A CCAM scenario that produces a positive average result may still disadvantage a particular group. Population heterogeneity is represented using characteristics observed in the population survey where the available sample supports such analysis. These include age, gender, educational attainment, employment status, residential context, driving-licence possession, household vehicle ownership, existing travel behaviour, technological confidence and self-perceived innovation-adoption profile.

Age is relevant because it may influence travel needs, driving ability, digital confidence and the perceived usefulness of different services. Older people could benefit from automated mobility if it extends their ability to travel independently. At the same time, unfamiliar interfaces, limited human assistance or low confidence in automated systems may create barriers. The model therefore does not assume that older age produces either a uniformly positive or negative effect. Instead, it allows potential accessibility benefits to coexist with adoption barriers. Gender may interact with travel patterns, household responsibilities, safety perceptions and employment exposure. Although gender differences should not be treated as inherent or fixed, their inclusion makes it possible to identify whether deployment scenarios produce uneven outcomes given current mobility patterns and social roles.

Education and technological confidence provide information about an individual's capacity and willingness to interact with emerging digital mobility systems. Users who are more confident with technology may adopt app-based automated services earlier. Individuals with limited digital confidence may require alternative booking channels, clearer information or human support. If these options are absent, digitalisation may reduce effective accessibility even when physical service coverage improves. Residential context is used to distinguish among city-centre, other urban, suburban and village environments. This captures differences in existing transport supply, trip distances and probable CCAM deployment conditions. It also supports exploration of the territorial distribution of benefits. Automated services may scale more quickly in urban areas, while their relative social value could be substantial in less-connected locations.

Existing travel behaviour provides another source of heterogeneity. People who frequently drive alone, use public transport or rely on other people for mobility may respond differently to CCAM services. Household vehicle ownership and driving-licence possession also affect the relevance of each use case. For example, an automated public or on-demand service may produce a larger accessibility benefit for a non-driver than for someone who already has unrestricted access to a private vehicle. Employment status is relevant to both travel patterns and exposure to labour-market transformation. Employed respondents may place greater value on travel-time reliability and commuting applications. Retired people, students and people outside employment may have different temporal and spatial travel requirements. However, the survey does not provide the detailed occupational information needed to estimate direct job-displacement exposure for every respondent. Employment-related effects are therefore represented at a broader sectoral and scenario level.

Some socially important groups cannot be modelled directly from respondent characteristics alone. The survey measured perceptions regarding accessibility for people with special mobility needs and other potentially underserved groups but did not necessarily identify respondents as members of each group. In these cases, the model uses the direction of perceived effects together with stakeholder and desk-based evidence. It does not present these responses as direct estimates of the behaviour of people with disabilities or low-income households. Social equity is consequently treated as a cross-cutting analytical perspective. The relevant question is not only whether an indicator improves but also whether the improvement is distributed across groups and territories. Where the data permit, the model compares adoption and outcome trajectories across observed population characteristics. Where direct subgroup data are limited, distributional implications are examined through scenario assumptions and sensitivity testing. Table 3 presents the population heterogeneity and its representation in the social impact assessment model.

Table 3: Population heterogeneity and its representation in the social impact assessment model

Population characteristic or group	Relevance to CCAM social impacts	Evidence available from D4.6	Representation in the model

Age	Age may influence travel needs, driving ability, technological confidence, perceived safety and the value of independent mobility.	Respondents were classified into age groups, allowing differences in willingness to use and perceived impacts to be examined. The survey also assessed perceived accessibility effects for older people.	Age is included as a population characteristic influencing use-case-specific adoption. Accessibility outcomes can also be compared across age categories.
Gender	Gender can be associated with different travel patterns, household responsibilities, personal-safety concerns and exposure to employment changes.	Gender was collected directly, with quotas used during sampling.	Gender can be included as an explanatory and segmentation variable in the analysis of adoption and perceived impacts.
Employment status	Employment influences trip purpose, travel frequency, scheduling needs and possible exposure to labor-market changes.	Respondents reported whether they were employed full-time or part-time, studying, retired, not working or engaged in other activities.	Employment status is used to distinguish travel needs and adoption patterns. Broader employment impacts are represented at sectoral and scenario levels.
Educational attainment	Education may affect familiarity with emerging technology, digital skills, access to CCAM-related employment and capacity to participate in reskilling.	The survey recorded respondents' highest educational level. Stakeholders also discussed education and training as determinants of workforce adaptation.	Education is represented as a factor influencing adoption and, where appropriate, access to emerging employment and training opportunities.
Technological confidence	Digital confidence may influence a person's capacity and willingness to book, monitor and use automated mobility services.	Respondents rated their confidence in using technology in everyday life.	Technological confidence is included as a determinant of willingness to use CCAM and as an indicator of possible digital exclusion.
Residential context	Urban, suburban and village residents experience different transport supply, trip distances, infrastructure conditions and likely CCAM deployment timelines.	Respondents identified whether they lived in a city center, elsewhere in a city, a suburb or a village.	Residential context influences assumptions concerning service availability, adoption and accessibility improvement.

Innovation-adoption profile	Innovators and early adopters may accept CCAM services earlier than late-majority or more hesitant users.	Respondents classified themselves as innovators, early adopters, early majority, late majority or laggards.	Innovation-adoption profile supports differentiation of adoption timing and diffusion across population segments.
Household vehicle ownership	Access to a private vehicle affects existing mobility options and the potential substitution of conventional travel by CCAM.	The survey collected the number of private cars available within the household.	Vehicle ownership is used as an indicator of baseline mobility resources and potential dependence on shared or public CCAM services.
Existing transport use	Current use of private cars, public transport, walking, cycling and other modes affects the relevance of different CCAM alternatives.	Weekly travel frequencies by transport mode were collected.	Existing travel behavior is used to establish baseline exposure and the potential for modal or service substitution.
Trip purpose	Work and non-work journeys may involve different requirements for reliability, flexibility, travel time and cost.	Willingness to use self-driving taxis and private automated cars was elicited separately for work and non-work travel.	Adoption can be differentiated by trip purpose for the relevant passenger use cases.
Delivery frequency	Existing reliance on home delivery affects the potential usefulness and uptake of automated delivery services.	Respondents reported the frequency with which they received deliveries and their willingness to use a delivery or pick-up robot.	Delivery frequency influences the potential adoption and substitution rate of automated delivery services.
People with lower incomes	Affordability may determine whether lower-income groups can access CCAM services and benefit from their deployment.	Stakeholders discussed affordability and the risk of unequal access. The population survey captured expected travel-cost changes but did not provide a sufficiently direct basis for comprehensive income-group estimation.	Lower-income implications are examined through affordability scenarios, pricing assumptions and distributional interpretation.
People living in underserved or rural areas	CCAM may improve mobility where conventional services are limited, but low demand and infrastructure constraints may delay deployment.	Residential context is observed in the survey, while stakeholders discussed geographical inequalities and service coverage.	Urban-first and territorially balanced deployment assumptions can be compared. Accessibility effects vary according to baseline service availability.

2.2.4 Principal Model Requirements

The combined evidence leads to several requirements for the social impact assessment model. First, the model must be dynamic. The effects of CCAM will emerge gradually and at different rates. Public acceptance, service availability, prices, skills development and employment transformation will not change simultaneously. The assessment must therefore represent stocks, flows, delays and feedback relationships over time.

Second, the model must be scenario-based. The future rate of CCAM penetration is uncertain, and the available evidence does not support a single deterministic forecast. Alternative assumptions are required concerning technological maturity, service introduction, public acceptance, operating costs and supportive measures. Third, the model must distinguish among use cases. Willingness to use and social effects differ across private, shared, public transport and freight applications. A single aggregated CCAM-adoption variable would conceal these differences.

Fourth, the model must allow population heterogeneity. Adoption and social outcomes should vary according to relevant population characteristics rather than being represented only by an average individual. Fifth, perceived and material outcomes must be distinguished. Survey responses concerning safety, accessibility or employment represent expectations. They influence acceptance and support the direction of model relationships but are not equivalent to observed changes in accidents, accessibility levels or jobs.

Sixth, the model must include feedback. Higher service uptake can produce economies of scale, which may lower costs and further increase adoption. Improved perceived safety can strengthen trust, while incidents may reduce it. Expanded accessibility can increase travel participation, which may affect service demand and the viability of additional provision. Employment displacement can increase demand for retraining, while the availability of training can affect the duration and severity of labor-market disruption. Seventh, the model must recognize implementation conditions. The same level of technological penetration could generate different social outcomes depending on pricing, accessible design, geographical coverage, public support and the availability of human assistance. These conditions are represented through scenario parameters and model relationships.

Finally, the model must remain interpretable. The purpose of the assessment is to support understanding of possible social effects and trade-offs. A highly complex structure that cannot be explained to stakeholders would limit the usefulness of the results. The selected variables and relationships are therefore designed to balance analytical coverage with transparency.

2.3 Social-impact Domains and Indicators

The final stage in defining the analytical scope involves consolidating the evidence into a set of social-impact domains and indicators. The indicator framework provides the connection between the conceptual relationships described above and the quantitative modelling presented in the following section.

Indicator selection followed several principles. Indicators should be relevant to the objectives of WP4C, traceable to the evidence generated within the project, sensitive to changes in CCAM deployment and interpretable by stakeholders and decision-makers. They should also avoid unnecessary duplication. Where several survey variables describe closely related effects, they can be represented through a common domain while retaining individual measures were analytically useful. The framework distinguishes among three types of variables:

- Drivers and scenario inputs, such as CCAM penetration, technological maturity, service cost and deployment timing;

- Intermediate variables, such as willingness to use, service uptake, trust, substitution and skills availability; and
- Social-impact outputs, such as accessibility, affordability, employment transformation, well-being and safety.

A preliminary summary of the indicator framework is presented below.

Table 4: Summary of indicator framework

Social-impact domain	Principal indicators	Role in the assessment
Affordability	Passenger travel cost; delivery cost; uptake response to price	Assessment of financial access to CCAM services
Adoption and participation	Willingness to use; uptake; trip or delivery substitution	Intermediate mechanism connecting deployment to social outcomes
Mobility and accessibility	Number of trips; travel time; service access; accessibility for different groups	Assessment of mobility opportunities and participation
Employment and skills	Job displacement; transformed roles; emerging jobs; reskilling needs	Assessment of workforce transition
Inclusion and equity	Differences in adoption, accessibility and cost across groups and locations	Distributional assessment across all domains
Well-being and safety	Travel stress; accidents; fatalities; perceived safety	Assessment of personal and societal welfare effects
Spatial effects	Residential-location change; potential urban-sprawl pressure	Assessment of longer-term indirect consequences

3 Social Impact Assessment Model

3.1 Purpose and overall modelling framework

The CCAM-ERAS social impact assessment model was developed to examine how the deployment of Cooperative, Connected and Automated Mobility technologies and services may influence different population groups and social outcomes over time. The model translates the evidence presented in Section 2 into a structured analytical framework capable of representing alternative deployment pathways, interactions among social-impact domains and differences among CCAM use cases. The model does not attempt to predict a single definitive future for CCAM. The timing, scale and geographical distribution of deployment remain uncertain, particularly for services operating at higher levels of automation. Instead, the model provides a scenario-based environment through which the consequences of different assumptions can be explored. Its forecasts are conditional on the technological, behavioral and policy conditions represented in each scenario.

The modelling framework combines three complementary analytical elements:

- Statistical analysis of the CCAM-ERAS population data, used to examine willingness to use different services, population heterogeneity and the perceived direction of selected social impacts.
- Forecasting of contextual and social variables, used to extend relevant historical trends over the short, medium and long term.
- System dynamics modelling, used to represent feedback relationships, accumulations, delays and interactions among CCAM penetration, adoption and social outcomes.

This combination is necessary because the social effects of CCAM cannot be represented adequately through a static calculation. Technological penetration, public acceptance, affordability, accessibility and workforce adaptation evolve at different rates and influence one another. For example, the availability of a self-driving service may initially increase faster than public adoption. Greater adoption may subsequently support economies of scale, which could reduce service costs and encourage additional use. Conversely, high costs or limited confidence may prevent the service from reaching a sufficient scale, delaying its broader social benefits. The model is informed by the system dynamics approaches previously applied in the MOVE2CCAM project. However, the corresponding model components are revised and enhanced for the purposes of CCAM-ERAS. The present framework places greater emphasis on stakeholder expectations, population-group differences, social inclusion, accessibility, employment transition and the conditions affecting public adoption. It therefore constitutes an extension of the previous modelling logic rather than a reproduction of the MOVE2CCAM model or its digital tool. The overall architecture consists of five connected layers:

- an evidence layer, containing primary and secondary data;
- a scenario layer, defining technological penetration, automation levels and deployment conditions;
- an adoption layer, estimating the willingness and capacity of different population groups to use each CCAM service;
- a social dynamics layer, representing the relationships between adoption and the selected social-impact domains; and
- an output layer, reporting projected indicators across use cases, population groups, scenarios and time horizons.

A graphical representation of this architecture is illustrated below.

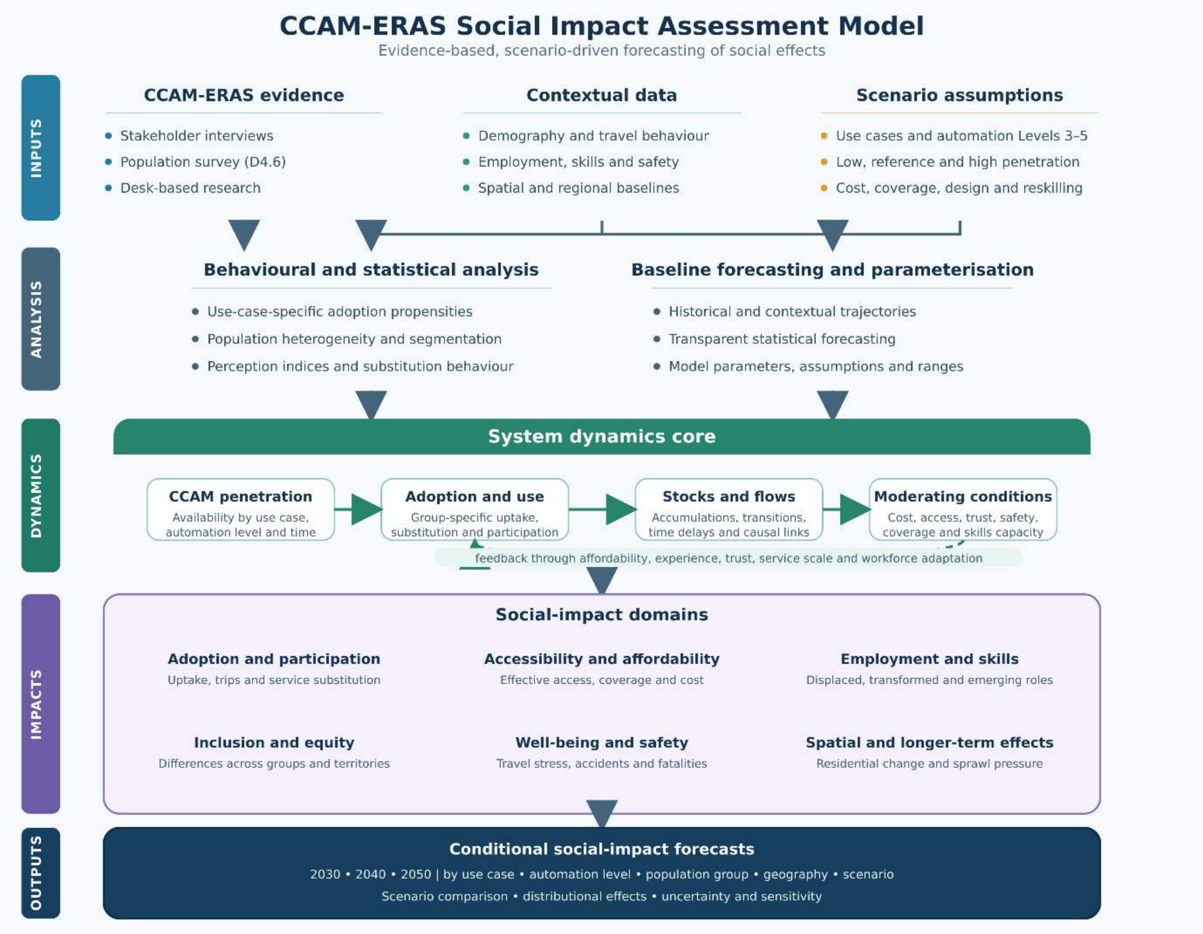

Figure 1: Graphical representation of architecture

3.2 Model Boundaries and Unit of Analysis

Defining the model boundaries is necessary to ensure that the assessment remains transparent and interpretable. CCAM deployment may affect a wide range of environmental, economic, technological and institutional outcomes. D4.7 does not attempt to reproduce a complete transport, macroeconomic or land-use model. Its primary concern is the representation of selected social effects and the mechanisms through which these effects may evolve. The model boundary begins with the availability and penetration of a CCAM use case. Technological development itself is not modelled from first principles. Instead, the introduction and subsequent penetration of each automation level are specified through scenarios and supported, where appropriate, by historical trends, public expectations and external evidence.

Within this boundary, the model represents how the availability of a CCAM service interacts with:

- willingness to use the service;
- technological confidence and public acceptance;
- service cost and affordability;
- service coverage and effective accessibility;
- existing travel behavior;
- employment exposure and task automation;
- the availability of reskilling opportunities;
- perceived and modelled safety effects;
- travel-related well-being; and
- selected longer-term spatial effects.

The principal unit of analysis is defined by four dimensions: (u, g, r, t), where:

- u represents the CCAM use case;
- g represents a population group or population profile;
- r represents the geographical context; and
- t represents time.

The use-case dimension distinguishes among self-driving taxis, private self-driving cars, automated public buses, automated on-demand shuttles and private delivery or pick-up robots. The population dimension allows the model to represent differences associated with age, gender, education, employment status, residential context, technological confidence, driving-license possession, vehicle ownership and existing travel behavior. Not every possible combination of these characteristics is modelled as a separate group. Such an approach would create very small samples and unstable estimates. Instead, characteristics are introduced through statistical relationships or through a limited number of analytically meaningful population profiles.

The geographical dimension provides the contextual baseline within which deployment occurs. It may represent a country, region or other area for which the required baseline variables are available. Country-level differences from the CCAM-ERAS survey can inform the analysis, but the model does not assume that all variation in behavior is explained by country alone. The temporal dimension allows the effects to be reported over short-, medium- and long-term horizons. The core reporting years correspond to 2030, 2040 and 2050, while intermediate values can be produced where required. These horizons are consistent with the implementation periods considered in the population survey and allow gradual changes in penetration, acceptance, accessibility and workforce adaptation to be represented.

The model distinguishes between endogenous and exogenous variables. Endogenous variables are influenced by other components within the model and may change through feedback relationships. Examples include service uptake, perceived acceptance, skills gaps and the number of workers transitioning between occupational categories. Exogenous variables are defined outside the model or through the scenario configuration. These include the assumed introduction year, maximum technological penetration, the cost of the service relative to the conventional alternative and selected baseline socio-economic trends.

Table 5: Variable categories

Variable category	Examples	Treatment
Exogenous scenario variables	Introduction year, maximum CCAM penetration, automation level, service coverage, relative service cost	Defined separately for each scenario
Contextual variables	Population, employment, conventional transport use, vehicle ownership, baseline accident levels	Obtained or forecast from secondary data
Behavioral variables	Willingness to use, technological confidence, substitution propensity	Estimated from the population evidence
Dynamic intermediate variables	Adoption, service scale, perceived accessibility, skills gap	Calculated within the model over time
Social-impact outputs	Accessibility, affordability, employment transformation, reskilling needs, travel stress, accidents and fatalities	Reported by use case, group, region and year

3.3 Causal Structure of the Social Impact Assessment

The social impact assessment model is organised around a set of causal mechanisms derived from the evidence presented in Section 2. These mechanisms describe how a change in one variable may influence another and how feedback may amplify, delay or balance the initial effect.

The relationships are represented through causal loop diagrams before being translated into mathematical equations. A positive causal link indicates that, all other conditions being equal, an increase in one variable produces an increase in another. A negative link indicates that an increase in one variable produces a decrease in another. The signs do not imply whether a relationship is socially beneficial; they describe only its direction.

The final causal loop diagram is presented below, and it is discussed in more detail in the subsequent subsections:

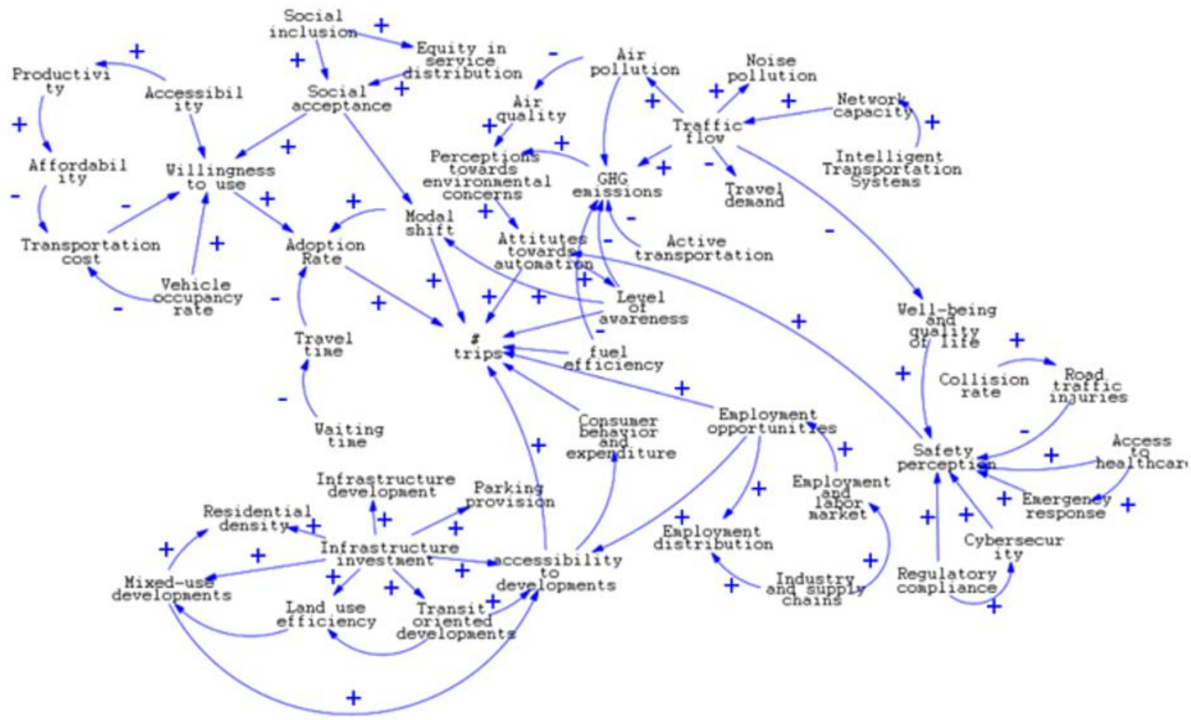

Figure 2: Final causal loop diagram

3.3.1 CCAM Penetration, Acceptance and Adoption

The first causal mechanism concerns the relationship between service availability and public adoption. Technological penetration increases the number of people who can potentially use a CCAM service, but availability alone does not guarantee uptake. Adoption also depends on perceived usefulness, affordability, safety, technological confidence, travel needs and the attractiveness of the service relative to existing alternatives. A reinforcing feedback loop may emerge between adoption and service scale:

CCAM availability → adoption → service demand → service scale → lower unit cost → affordability → adoption

As more people use a service, operators may achieve economies of scale. If these savings result in lower fares, shorter waiting times or wider coverage, the service becomes attractive to additional users. This can produce a reinforcing diffusion process. A balancing loop may also occur:

CCAM adoption → service demand → congestion or capacity pressure → reduced service quality → lower adoption

If rapid adoption is not accompanied by appropriate operational capacity, waiting times, empty-vehicle movements or congestion may increase. These effects can reduce service attractiveness and limit further adoption. Acceptance may change through experience. Successful operation and visible safety improvements can increase confidence, whereas incidents, technical failures or unclear responsibility may reduce it. The model therefore treats acceptance as a variable that can evolve rather than as a fixed characteristic established at the beginning of the simulation.

3.3.2 Accessibility and affordability

The second mechanism concerns effective accessibility. CCAM can expand mobility opportunities by providing services to people who cannot drive or who live in areas with limited conventional transport. However, the accessibility benefit depends on more than the physical presence of an automated vehicle. Effective accessibility is represented as a function of:

- geographical service coverage;
- service availability and operating hours;
- physical accessibility of vehicles and boarding locations;
- availability of human or remote assistance;
- accessibility of booking and payment systems;
- service cost;
- technological confidence; and
- the suitability of the service for the user’s trip.

A reinforcing relationship may emerge between improved accessibility and service demand: Service coverage → accessibility → travel participation → demand → service viability → service coverage

If CCAM allows previously underserved users to make additional journeys, higher demand may support wider service provision. However, this relationship is not guaranteed. In low-density areas, the increase in demand may remain insufficient to support commercial provision. Public support or service obligations may therefore affect whether accessibility improvements are sustained. Affordability moderates the relationship between availability and accessibility. A technically accessible service may remain unavailable in practice to users who cannot afford it. The model distinguishes between general availability and effective access by introducing a cost-related factor. Higher service prices reduce adoption, with the strength of this effect varying among population groups and service types.

The D4.6 population survey generally asked respondents to consider automated services with costs and travel times comparable to conventional alternatives. These responses provide a reference level of adoption. Scenario-specific adjustments are subsequently applied when automated services are assumed to be more or less expensive than the corresponding conventional mode.

3.3.3 Employment Transformation and Skills

The employment mechanism represents the gradual effect of automation on occupational tasks and workforce requirements. Increasing CCAM penetration can reduce demand for certain conventional driving activities, but the relationship is neither immediate nor uniform. Three employment effects are distinguished:

- Displacement, where an existing occupational role or set of tasks is no longer required;
- Transformation, where the occupation remains but its task composition and required skills change; and

- Creation, where new occupations or employment opportunities emerge.

The principal balancing relationship concerns reskilling: Automation → exposed jobs → job displacement → demand for reskilling → trained workers → transition to transformed or emerging jobs

If training capacity is available and workers can participate, the increase in reskilling reduces the number of workers remaining displaced. If training provision is delayed, inaccessible or poorly aligned with employer demand, a skills gap may persist. A second relationship connects CCAM market development with new employment:

CCAM penetration → service and infrastructure investment → demand for technical and supervisory skills → new employment opportunities

The creation of new jobs does not automatically compensate for displaced roles. New positions may require different qualifications, may be located in different regions and may emerge later than the initial displacement. The model therefore represents job displacement and job creation as separate processes. The extent of employment exposure also varies by automation level. Level 3 automation retains a significant human fallback role and is expected to transform driving tasks more than eliminate them. Level 4 operation may reduce the need for an onboard driver within a defined operational domain but can increase demand for remote supervision and operational support. Level 5 automation represents the greatest theoretical potential for task substitution but is also subject to the highest uncertainty over the modelled period.

3.3.4 Safety and Travel-related Well Being

Safety is both a determinant of adoption and a potential outcome. Public confidence may increase when automated systems are perceived as reliable and capable of reducing human error. At the same time, wider deployment may produce actual changes in accidents and fatalities. The corresponding feedback relationship can be represented as:

CCAM penetration → system exposure and operational experience → safety performance → perceived safety → adoption → CCAM penetration

The relationship may be reinforcing when safety performance is positive. It may operate in the opposite direction following incidents or visible technical failures. The model distinguishes between perceived safety and modelled safety outcomes. The former is derived from population attitudes and influences adoption. The latter represents projected changes in accidents and fatalities under assumptions concerning automation performance, exposure and the share of traffic undertaken by CCAM vehicles.

Travel-related well-being includes stress associated with driving, navigation, parking, waiting and unreliable services. Automated passenger services may allow users to avoid some of these burdens. However, unfamiliar systems, absence of human assistance or concern about technical reliability may increase stress for some groups. The net effect is therefore linked to technological confidence, service reliability and perceived safety.

3.3.5 Spatial and Longer-term Effects

CCAM may influence residential location by changing the perceived cost and burden of travelling. If travelers can use journey time for work or leisure, or if door-to-door services make longer journeys easier, some households may become more willing to live farther from employment and services. The causal relationship can be summarized as:

CCAM availability → lower perceived travel burden → acceptance of longer journeys → residential relocation pressure → longer average trips

This may create a reinforcing relationship if longer-distance settlement patterns increase dependence on motorized or automated mobility. However, the magnitude of this effect is uncertain and is expected to emerge gradually. Residential relocation is consequently represented as a secondary long-term effect and interpreted cautiously.

3.4 Data Inputs and Model Parameterization

The model uses primary evidence from CCAM-ERAS, contextual information from secondary sources and explicit scenario assumptions. The parameterisation process distinguishes carefully between observed values, public perceptions and assumptions regarding future technological development.

3.4.1 Primary CCAM-ERAS evidence

The principal primary inputs are derived from the population survey and stakeholder interviews described in D4.6. Population survey inputs include:

- use-case-specific willingness to use;
- willingness to use services for work and non-work journeys;
- willingness to purchase or lease a private self-driving car;
- expected implementation year;
- expected trip or delivery substitution;
- existing travel behavior;
- technological confidence;
- innovation-adoption profile;
- socio-demographic characteristics; and
- perceived direction of selected social impacts.

Stakeholder evidence informs:

- the direction and structure of causal relationships;
- assumptions concerning employment transformation;
- time delays in training and workforce adaptation;
- conditions affecting accessibility and affordability;
- possible new occupations and skills requirements;
- institutional and operational constraints; and
- the identification of scenario parameters.

Qualitative stakeholder evidence is not converted mechanically into numerical coefficients. It is used to establish whether a relationship should be represented, whether it is likely to be positive or negative and which external conditions may alter it.

3.4.2 Secondary and Contextual Data

Secondary data provide baseline values and historical trends for variables that cannot be obtained from the population survey. Depending on geographical availability, these may include:

- population and demographic structure;
- employment by economic sector and occupation;
- unemployment;
- education and training participation;
- vehicle ownership;
- transport modal split;
- passenger and freight activity;
- transport expenditure;

- road accidents and fatalities;
- urbanization and population density; and
- selected indicators of digital access or technological readiness.

Historical observations are harmonized to a common time structure and geographical unit. Where the original source uses different definitions or geographical classifications, variables are transformed or documented before they are used in the forecasting component. The model does not assume that all secondary variables are directly affected by CCAM. Some provide baseline trajectories against which the incremental effect of a CCAM scenario is assessed.

The list of parameters utilized from external repositories and sources beyond the project, such as Eurostat that provide supplementary insights and fills gaps into the data and model assumptions that may not be covered by the primary data are provided below.

Table 6: List of parameters from secondary data collection

Parameters	Measurement Units	Description
Passenger Cars	absolute number	the number of passenger cars
Passenger Vehicle-Km	million kilometers	Million vehicle kilometers using passenger cars
Train/Bus Vehicle-Km	million kilometers	Million vehicle kilometers using train or bus
Walking-Km	million kilometers	Million kilometers covered for pedestrians
Cycle-Km	million kilometers	Million vehicle kilometers for micro-mobility
Modal-Car	percentage	Modal split for passenger cars
Modal-Public Transport	percentage	Modal split for public transportation modes
Modal-Walk	percentage	Modal split for walking
Modal-Cycle	percentage	Modal split for micro-mobility
Charging Stations	absolute number	the number of public charging stations for electric vehicles
Renewable energy	percentage	the percentage of using renewable energy sources
Vehicle fuel efficiency	thousand tons of oil equivalent	The vehicle fleet's fuel efficiency is quantified at thousand tons of oil equivalent (ktoe) per million vehicle kilometers traveled, indicating the total energy consumption derived from oil required to cover this distance
Air emissions	tCO2 equivalent	Total air emissions quantified at tons of CO2 equivalent (tCO2e), representing the total greenhouse gases emitted, standardized to the global warming potential of carbon dioxide
GDP	million Euros	Gross Domestic Product
Infrastructure investment	kilometers	The infrastructure investment of road and rail navigable networks measured in kilometers
Unemployment rate	percentage	The percentage of unemployed people
Skilled jobs	thousand people	The number of skilled jobs measured in thousand people including employment in technology and knowledge-intensive sectors
Cyber attacks	absolute number	The number of cyber-attacks from online threats
Road fatalities	percentage	The crude death rate of road fatalities is measured as the number of road fatalities per 100,000 people
Road injuries	absolute number	The number of road accidents

Number of hospital beds	absolute number	The number of beds in hospitals
Disposable income	million purchasing power standards	The disposable income of households is quantified at million purchasing power standards (PPS), reflecting the total income available for spending and saving after accounting for taxes and social contributions, adjusted for price level differences across regions
Electric Passenger Cars	percentage	the number of electric passenger cars
Number of Parcels	absolute number	the number of parcels delivered
Passenger Cars	absolute number	the number of passenger cars
Passenger Vehicle-Km	million kilometers	Million vehicle kilometers using passenger cars
Train/Bus Vehicle-Km	million kilometers	Million vehicle kilometers using train or bus

3.4.3 Treatment of Ordinal Perception Data

Several survey questions use five-point ordinal scales. Willingness-to-use questions range from highly unlikely to highly likely, while impact questions range from significant reduction to significant increase or improvement. These categories indicate order but do not necessarily represent equal distances. Descriptive summaries can assign numerical codes for presentation, but the statistical analysis retains the ordinal nature of the response where possible.

For use in the system dynamics component, a normalized perception index may be calculated as:

$$PI_{kgr} = \frac{\sum_{c=-2}^{2} c * p_{kgcr}}{2}$$

where:

PIkgr is the perception index for indicator k, group g and region r;

c is the response category from −2 to 2; and

Pkgrc is the proportion of respondents selecting category c.

The resulting index ranges from −1 to 1. A negative value indicates an expected reduction or deterioration, zero indicates no average directional change and a positive value indicates an expected increase or improvement. This index is not interpreted as the percentage change that will occur in the corresponding real-world indicator. It is used as a measure of the direction and relative strength of public expectations. The magnitude of the forecast effect is determined through the broader model structure, external data and scenario assumptions.

3.4.4 Treatment of Implementation Expectations

The survey asked respondents to indicate whether selected services would be introduced in 2030, 2035, 2040, 2045, 2050 or never. The “never” category is not coded as a year after 2050 because it represents a qualitatively different expectation. The timing responses are used to construct a distribution of public expectations concerning service maturity. They may influence the initial adoption curve or support scenario timing, but they do not replace technical deployment assumptions. Citizens may underestimate or overestimate the speed of technological development, and expectations may differ from actual regulatory or market conditions.

3.4.5 Harmonization and Missing-data Treatment

Before analysis, the data are checked for incomplete responses, inconsistent coding and implausible values. Categorical variables are harmonised across the five national samples, and the direction of ordinal scales is checked to ensure consistent interpretation. Missing values are treated according to the type and extent of missingness. Where a limited number of observations lack a non-essential explanatory variable, complete-case estimation may be used. Where omission would materially reduce the sample or distort its composition, an appropriate imputation or missing-category approach can be applied and documented.

Country samples are analysed with attention to their different sizes. Pooled estimates may include country-specific effects, while country-level outputs should report uncertainty and avoid drawing strong conclusions from small percentage differences.

3.5 Statistical Representation of Adoption and Population Heterogeneity

The adoption component estimates how willingness to use a CCAM service varies according to use case, population characteristics and contextual conditions. Because the survey responses are ordinal, ordered-response models provide an appropriate starting point.

Let the unobserved propensity of individual n to use service u be:

$$A_{nu}^{*} = a_u + \beta_u X_n + \gamma_u T_n + \delta_{ur} + \varepsilon_{nu}$$

where:

- A_{nu}^{*} is the latent adoption propensity;
- α_u is a use-case-specific constant;
- X_n contains socio-demographic and residential characteristics;
- T_n contains travel-behaviour and technology-related characteristics;
- δ_{ur} captures contextual or country-specific effects; and
- ε_{nu} is an unobserved error term.

The observed willingness category is determined by threshold values:

$$A_{nu} = c \text{if} \mu_{c-1} < A_{nu}^{*} \leq \mu_c$$

This formulation allows the probability of each response category to be estimated without assuming that the distance between “somewhat unlikely” and “neutral” is identical to the distance between “neutral” and “somewhat likely”.

Where the same respondent evaluates multiple services, the observations are not fully independent. This can be addressed through respondent-level effects, clustered standard errors or correlated error structures, depending on the final model specification and sample size.

The statistical analysis can include the following explanatory characteristics supported by the data:

- age;
- gender;
- education;
- employment status;
- residential context;

- driving-license possession;
- vehicle ownership;
- existing transport use;
- delivery frequency;
- technological confidence; and
- innovation-adoption profile.

Interactions can be included selectively where there is a clear analytical justification. For example, the effect of age may vary according to technological confidence, and the effect of village residence may vary according to vehicle ownership. Excessive interaction terms should be avoided because they can create unstable estimates, particularly within the smaller national samples.

The resulting probabilities are aggregated into group-specific adoption propensities. If $Pr(A_{nu} \geq 4)$represents the probability of being somewhat or highly likely to use service u, then the initial adoption propensity for group $g$can be expressed as:

$$\pi_{ugr} = Pr(A_u \geq 4 \mid g, r)$$

The propensity π_{ugr}does not represent the actual share of the group using the service in a future year. It represents willingness under the conditions described in the survey. Actual adoption also depends on technological availability, service coverage, cost and scenario conditions.

Where the statistical evidence does not support detailed subgroup estimation, broader segments can be used. Possible segments include:

- technologically confident early adopters;
- mainstream users with conditional acceptance;
- digitally cautious users;
- private-car-oriented users;
- public or shared-mobility-oriented users; and
- users with high potential accessibility benefits.

These segments should be interpreted as analytical groupings rather than fixed social identities.

3.6 System Dynamics Formulation

The system dynamics component translates the evidence and statistical relationships into time-dependent equations. It represents how CCAM penetration, adoption and social outcomes accumulate and interact over the modelling period.

3.6.1 CCAM Penetration

The penetration of each use case and automation level can be represented using a logistic diffusion function:

$$P_{ulr}(t) = \frac{K_{ulr}}{1 + \exp\left[-\lambda_{ulr}(t - \tau_{ulr})\right]}$$

where:

- $P_{ulr}(t)$is the penetration of use case u, automation level $l$and region $r$at time t;
- $K_{ulr}$is the maximum penetration assumed under the scenario;

- λ_{ulr} determines the speed of diffusion; and
- τ_{ulr} represents the midpoint of the diffusion process.

The parameters vary across the low-, reference- and high-penetration scenarios. A delayed scenario has a later midpoint and lower diffusion rate, whereas an accelerated scenario has an earlier midpoint and faster growth.

3.6.2 Population Group Adoption

The number or share of users from population group g is represented as a stock:

$$U_{ugr}(t)$$

The stock changes through adoption and discontinuation flows:

$$\frac{dU_{ugr}(t)}{dt} = I_{ugr}(t) - O_{ugr}(t)$$

where:

- $I_{ugr}(t)$ is the inflow of new users; and
- $O_{ugr}(t)$ is the outflow of users discontinuing the service.

The adoption inflow is expressed as:

$$I_{ugr}(t) = \left[N_{gr}(t) - U_{ugr}(t)\right] \cdot P_{ulr}(t) \cdot \pi_{ugr} \cdot AF_{ugr}(t)$$

where:

- $N_{gr}(t)$ is the relevant population of group g;
- $P_{ulr}(t)$ represents technological and service availability;
- π_{ugr} is the group-specific adoption propensity; and
- $AF_{ugr}(t)$ is an adjustment factor representing affordability, accessibility, perceived safety and service quality.

The adjustment factor can be expressed as:

$$AF_{ugr}(t) = w_1 C_{ur}(t) + w_2 AC_{ugr}(t) + w_3 PS_{ugr}(t) + w_4 TC_g$$

where:

- $C_{ur}(t)$ represents cost attractiveness;
- $AC_{ugr}(t)$ represents effective accessibility;
- $PS_{ugr}(t)$ represents perceived safety;
- TC_g represents technological confidence; and
- $w_1, \ldots, w_4$ are normalised weights.

Where necessary, the combined value is transformed to remain between zero and one.

3.6.3 General Social Impact Equation

For a social indicator k, the projected value can be expressed generally as:

$$Y_{kgr}(t) = Y_{kgr}^0(t) + \sum_{u=1}^{U} \theta_{ku}\ E_{ugr}(t)\ M_{kugr}(t)$$

where:

- $Y_{kgr}^0(t)$ is the baseline trajectory without the additional CCAM effect;

- θ_{ku}represents the relationship between use case $u$and indicator k;
- $E_{ugr}(t)$represents exposure to or use of the CCAM service; and
- $M_{kugr}(t)$represents moderating conditions such as affordability, inclusive design, automation level or policy support.

This formulation permits the same level of penetration to generate different social outcomes under different deployment conditions.

3.6.4 Accessibility

Effective accessibility can be represented as:

$$AC_{ugr}(t) = P_{ur}(t) \cdot SC_{ur}(t) \cdot PD_{ugr}(t) \cdot DA_{ugr}(t) \cdot FA_{ugr}(t)$$

where:

- $SC_{ur}(t)$is geographical and temporal service coverage;
- $PD_{ugr}(t)$represents physical and service-design accessibility;
- $DA_{ugr}(t)$represents digital accessibility; and
- $FA_{ugr}(t)$represents financial accessibility.

This multiplicative formulation reflects the fact that a severe barrier in one component can substantially reduce effective accessibility. For example, broad service coverage does not provide full accessibility if the booking system is unusable for a particular group.

3.6.5 Employment and Skills

Let $E_{sr}(t)$represent employment in occupational or sectoral category s. Its change is expressed as:

$$\frac{dE_{sr}(t)}{dt} = J_{sr}^{new}(t) + J_{sr}^{transition}(t) - J_{sr}^{displaced}(t) - J_{sr}^{exit}(t)$$

The number of jobs exposed to displacement is related to automation penetration and task exposure:

$$J_{sr}^{displaced}(t) = E_{sr}(t) \cdot TE_s \cdot P_{lr}(t) \cdot [1 - M_s(t)]$$

where:

- $TE_s$is the proportion of tasks potentially exposed to automation; and
- $M_s(t)$represents mitigation through task transformation, gradual deployment or continued human involvement.

The stock of workers requiring reskilling can be expressed as:

$$\frac{dR_{sr}(t)}{dt} = J_{sr}^{displaced}(t) + J_{sr}^{transformed}(t) - J_{sr}^{trained}(t)$$

Training completion depends on available capacity and participation:

$$J_{sr}^{trained}(t) = \min\left[R_{sr}(t), TC_{sr}(t)\right] \cdot PR_{sr}(t)$$

where $TC_{sr}(t)$is training capacity and $PR_{sr}(t)$is the participation or successful-completion rate.

These equations allow scenarios with limited training provision to be compared with scenarios involving earlier and more comprehensive workforce preparation.

3.7 Forecasting of Baseline and Contextual Variables

The system dynamics equations require baseline trajectories for selected contextual variables. Forecasting is used where historical observations are available and where the variable is expected to evolve independently of the CCAM scenario.

The forecasting process consists of the following stages:

- collection and harmonization of historical data;
- inspection of missing values, structural breaks and outliers;
- estimation of alternative forecasting specifications;
- comparison of model performance;
- selection of an interpretable and sufficiently robust specification; and
- production of baseline projections to 2050.

The selection of forecasting techniques is determined by data availability, time-series length and the expected form of the relationship. Linear trends and multiple linear regression are suitable where the variables exhibit stable and interpretable relationships. Autoregressive approaches can be used where the historical development of a variable provides relevant information about its future values.

More complex machine-learning approaches may capture nonlinear relationships but are not necessarily preferable for the present assessment. Many regional social indicators are available only as relatively short annual time series. Highly parameterized models may consequently overfit the historical data and produce unstable long-term forecasts. Interpretability is also important because the forecast values become inputs to a policy-oriented system dynamics model.

The selected forecasting approach therefore prioritizes:

- acceptable predictive performance;
- stability over the long-term horizon;
- transparency;
- compatibility with the system dynamics equations; and
- the ability to update projections when new data becomes available.

Model performance can be compared using measures such as:

$$MAE = \frac{1}{n}\sum_{t=1}^{n} \mid y_t - \hat{y}_t \mid$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}$$

and, where appropriate:

$$R^2 = 1 - \frac{\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}{\sum_{t=1}^{n}(y_t - \bar{y})^2}$$

The final method selected for each variable should be documented in a model parameter table, including the historical period, source, forecast specification and performance measure.

The CCAM-ERAS forecasting work enhances the previous modelling approach by introducing additional social variables and revised relationships informed by D4.6. These enhancements include population-group adoption propensities, effective accessibility, perceived impacts, employment-transition processes and reskilling delays.

3.8 Scenario Design

Scenario analysis is used to examine how social impacts change under different CCAM deployment pathways. The scenarios do not represent predictions that one particular future will occur. They define internally consistent combinations of assumptions. Three core penetration pathways are considered.

- Low-penetration scenario: The low-penetration scenario assumes delayed technological maturity, restricted operational domains and relatively slow public adoption. Service coverage remains concentrated in selected locations, and costs decline gradually. Level 3 applications remain important for longer, while Level 4 and Level 5 services achieve limited penetration by 2050. This scenario produces comparatively modest direct social effects, but it may also delay accessibility improvements and the emergence of new employment opportunities. Workforce disruption is slower, providing more time for adaptation, although investment in training may also remain limited.
- Reference-penetration scenario: The reference scenario assumes gradual but sustained development. Selected Level 4 services become increasingly available within defined operational environments, while more advanced applications expand over the medium and long term. Costs decrease as services mature, and public adoption follows a moderate diffusion pathway. This scenario represents the central set of assumptions against which the low- and high-penetration scenarios are compared.
- High-penetration scenario: The high-penetration scenario assumes earlier technological maturity, wider service coverage and faster diffusion. Highly automated services become available across a broader range of operational environments, and economies of scale reduce costs more quickly. Potential accessibility and safety effects appear earlier, but the pace of employment transformation is also faster. If reskilling and inclusive-service measures do not develop at a comparable rate, the high-penetration scenario may produce greater short- and medium-term distributional pressures.

3.9 Uncertainty and Sensitivity Analysis

Long-term social-impact forecasting is subject to substantial uncertainty. The technology is developing; regulation continues to evolve and large-scale evidence on behavioral adaptation remains limited. The model results should therefore be presented as ranges or conditional trajectories rather than precise predictions.

Uncertainty arises from four principal sources:

- Technological uncertainty, concerning the timing, capabilities and operating domains of automated systems;
- Behavioral uncertainty, concerning public acceptance, substitution and longer-term travel responses;
- Parameter uncertainty, concerning the numerical strength of relationships within the model; and
- Contextual uncertainty, concerning wider demographic, economic and transport-system developments.

Sensitivity analysis examines how the results change when influential assumptions are varied. The following parameters are particularly relevant:

- CCAM introduction year;
- maximum penetration;
- diffusion rate;
- adoption propensity;
- cost relative to conventional alternatives;
- service coverage;
- perceived and actual safety improvement;
- task-exposure rate;
- rate of job creation;
- training capacity;
- reskilling participation;
- digital-accessibility factor; and
- strength of residential-location response.

A one-at-a-time sensitivity test can be used to identify the effect of varying each parameter while holding the others constant. Where parameters interact strongly, combined scenarios or probabilistic analysis can be used.

The normalized sensitivity of output Y to parameter x can be calculated as:

$$S_{Y,x} = \frac{\Delta Y/Y}{\Delta x/x}$$

A value greater than one in absolute terms indicates that the output changes proportionally more than the parameter. The sign indicates the direction of the relationship. The assessment should distinguish between findings that remain stable across a wide range of assumptions and findings that depend strongly on uncertain parameters. Stable findings provide a stronger basis for policy interpretation. Highly sensitive findings should be presented as areas requiring monitoring, additional data or further investigation.

The sensitivity analysis is not intended to constitute the stakeholder validation of the model. It is an internal component of the modelling process that supports transparent interpretation of uncertainty. The structured validation of the model, its assumptions and its forecasts will be undertaken subsequently under Task 4.C.4 and reported in Deliverable D4.8.

4 Forecasting Results

4.1 Overview of the Modelled Scenarios

This section presents the forecast social effects of CCAM under the low-, reference- and high-penetration scenarios described in Section 3. The results cover the period to 2050, with particular attention to the short-, medium- and long-term horizons represented by 2030, 2040 and 2050. The forecasts are reported by CCAM use case and social-impact domain and, where the available evidence permits, by population characteristics and geographical context. The results should be interpreted as conditional projections rather than deterministic predictions. They show how selected indicators evolve when the assumptions concerning technological availability, public adoption, service cost, geographical coverage and automation level are applied consistently over time. Consequently, differences between scenarios should be understood as the combined effect of alternative deployment pathways and the behavioral and social relationships represented in the model.

The low-penetration scenario produces comparatively limited changes during the first two horizons. Technological availability develops gradually; service coverage remains concentrated in selected areas and adoption is restricted by limited exposure and slower reductions in service cost. Under these conditions, the potential social benefits of CCAM emerge slowly and remain unevenly distributed. The reference scenario produces a more gradual and sustained transition. Adoption increases as services become more available, technological confidence develops and costs approach those of conventional alternatives. The most visible changes occur during the medium-term period, when an increasing share of the population has access to CCAM services and the corresponding social effects become more clearly observable.

The high-penetration scenario generates earlier and larger changes across most social-impact domains. Wider service availability and faster adoption increase the potential for accessibility, safety and travel-related well-being improvements. However, faster deployment also accelerates employment transformation, service substitution and possible distributional pressures. A high level of technological penetration does not therefore generate an unconditionally superior social outcome. The final effect depends on whether affordability, accessibility, service coverage and workforce adaptation develop at a comparable pace. The results demonstrate that the rate of CCAM penetration is only one determinant of the eventual social effect. Implementation conditions are equally important. Similar penetration levels can produce different outcomes depending on whether deployment is concentrated in commercially attractive areas or extended to underserved locations, whether services are affordable, and whether digital and physical accessibility are incorporated into service design.

4.2 Adoption and Participation Across CCAM Use Cases

The forecast adoption trajectories follow a general diffusion pattern, with limited uptake during the early period, faster growth as services become more widely available and a gradual reduction in the rate of growth as adoption approaches the maximum level assumed in each scenario. Nevertheless, the timing and magnitude of this pattern differ substantially across use cases. Self-driving taxis and automated on-demand shuttles show strong potential among users seeking flexible mobility without purchasing a vehicle. Their uptake is particularly sensitive to cost, waiting time, service coverage and perceived safety. Under the low-penetration scenario, these services remain concentrated in selected operational areas, limiting their broader social effect. Under the reference and high-penetration scenarios, adoption increases as coverage expands and the services become more familiar.

The model indicates that automated taxis and shuttles may attract both substituted and newly generated journeys. Some users replace conventional taxi, private-car or public transport trips, whereas others make journeys that they previously postponed or did not undertake. The latter effect is particularly relevant for people with limited access to a private vehicle or to conventional public transport. Increased trip-making can therefore represent an accessibility improvement, although it may also contribute to additional vehicle activity if services are not coordinated with collective transport. The adoption of self-driving private cars follows a different trajectory. Willingness to use or purchase these vehicles is more closely related to existing car ownership, driving behavior, technological confidence and the perceived personal benefit of automation. Private automated vehicles become more attractive when users expect to reduce the effort associated with driving or make productive use of travel time.

In the high-penetration scenario, the model projects a stronger transition towards private automated vehicles among groups already oriented towards car use. This increases the potential convenience and independent mobility benefits of automation but may also reinforce private-car dependence. The outcome is particularly sensitive to the relationship between private automated vehicles and alternative shared or public services. Automated public buses generally produce a more gradual adoption pattern. Their use depends not only on acceptance of automation but also on existing public transport habits, route availability, frequency, reliability and the perceived need for human assistance. Where automated operation is used to expand operating hours, increase service frequency or provide routes that would otherwise be difficult to operate, the social benefit is larger than when automation merely replaces the driver without changing the passenger service.

For automated delivery, uptake is linked to current delivery frequency, familiarity with e-commerce and willingness to substitute conventional deliveries. The model projects faster adoption among people who already receive deliveries frequently. The corresponding increase in service use may partly replace conventional last-mile delivery activity, although lower delivery costs and greater convenience could also stimulate additional orders. Across all use cases, technological availability does not translate directly into adoption. The gap between the potential population covered by the technology and the population using it remains significant during the early stages. This gap narrows when costs decrease, service coverage improves and positive experience increases confidence.

Population characteristics influence the timing of this transition. Technologically confident respondents and those identifying as innovators or early adopters enter the adoption stock earlier. More cautious users enter later and are more dependent on evidence of safety, reliability and affordability. These differences are largest in the short term and generally decline as services become more familiar. However, diffusion does not remove all population differences. Groups facing financial, digital or physical barriers may remain less likely to use a service even under high penetration. This confirms the importance of distinguishing technological diffusion from socially inclusive adoption.

4.3 Accessibility, Affordability and Distributional Effects

Accessibility represents one of the most important potential social benefits identified by the model. All three scenarios generate some improvement, but the scale and distribution of this improvement vary considerably. Under low penetration, accessibility gains are concentrated among early adopters and within the areas where CCAM services are initially available. People living outside the initial operational areas receive limited benefit, even where their need for alternative mobility is substantial. This creates a difference between the potential social value of CCAM and the benefits realized during early deployment.

Under the reference scenario, accessibility improves progressively as automated taxis, buses and on-demand shuttles become more widely available. The effect is strongest where these services address a specific gap in the conventional transport system, such as first- and last-mile connections, off-peak travel or access from lower-density areas. The high-penetration scenario produces the largest potential increase in mobility opportunities. Nevertheless, the model shows that broad technological coverage is not sufficient to ensure effective accessibility. Vehicle design, digital interfaces, payment mechanisms, availability of assistance and service affordability determine whether different population groups can make practical use of the technology.

Automated public buses and shuttles produce comparatively strong accessibility benefits for non-drivers and users who cannot rely consistently on a private vehicle. Self-driving taxis provide flexible door-to-door mobility but may generate smaller distributional benefits if their prices remain substantially higher than public transport. Private automated cars improve accessibility primarily for households able to purchase or lease the vehicle, unless alternative ownership or sharing arrangements are introduced. Older people may obtain substantial benefits from highly automated services that do not require a driving license. These benefits are strongest when the service includes accessible booking methods, clear information and the possibility of obtaining human assistance. Where interaction is restricted to digital applications and no additional support is provided, the model projects a lower level of effective adoption among users with limited technological confidence.

Similar conditions apply to people with special mobility needs. Physical vehicle accessibility, boarding arrangements and the ability to communicate with the service are as important as geographical coverage. Scenarios incorporating accessible design therefore produce significantly stronger social outcomes than scenarios in which the same number of vehicles is deployed without specific accessibility measures. Affordability is one of the most influential moderating variables. When CCAM services cost more than their conventional alternatives, adoption declines and becomes concentrated among users with a greater willingness or ability to pay. This reduces the effective accessibility benefit and can widen the difference between early adopters and the wider population.

When costs approach those of conventional services, uptake increases substantially. The effect is especially pronounced for automated taxis, on-demand shuttles and delivery robots because users can adopt these services without making a large capital investment. If economies of scale or supportive pricing reduce costs further, the model produces stronger adoption and accessibility gains. However, lower prices may also increase the number of trips and encourage substitution away from walking, cycling or public transport. The model therefore identifies a trade-off between affordability-driven adoption and the wider transport-system consequences of increased demand. The social interpretation depends on whether additional journeys represent improved participation by underserved groups or unnecessary substitution of more sustainable transport modes.

The distributional results demonstrate that population averages can conceal important differences. A scenario may produce an overall improvement in accessibility while leaving digitally cautious users or people living outside the principal service areas with limited benefits. For this reason, group-specific and territorial results should be considered alongside the aggregate indicator. Market-led and urban-focused deployment generally produces faster initial uptake but wider spatial differences. More inclusive deployment assumptions generate slower or more costly expansion but distribute accessibility benefits more evenly. This suggests that the social performance of CCAM cannot be evaluated only through the number of users or vehicles. The distribution of access is equally important.

4.4 Employment Transformation and Skills Requirements

The employment results indicate that CCAM is more likely to transform the composition of transport-related work gradually than to produce an immediate disappearance of conventional occupations. The rate of change depends on the automation level, use case and deployment scenario. Under low penetration, the effects remain limited and are concentrated in pilot operations or defined operational environments. Human drivers and operators continue to perform most conventional tasks, although some responsibilities begin to shift towards system monitoring and passenger assistance.

Under the reference scenario, task transformation becomes more visible during the medium-term period. Driving-related responsibilities decrease within the areas where Level 4 services are introduced, while supervisory, technical and customer-support activities increase. The number of affected roles grows progressively rather than through a single transition point. The high-penetration scenario accelerates this process. A larger proportion of routine driving and delivery activity becomes exposed to automation, while demand increases for remote operations, fleet supervision, maintenance, data management and cybersecurity skills. The model does not assume that newly created roles automatically compensate for displaced ones. The timing, location and qualification requirements of the new jobs may differ from those of the roles affected.

The forecast skills effect is therefore more consistent than the net employment effect. Across the scenarios, increasing CCAM penetration produces greater demand for technical, digital and interdisciplinary competencies. The magnitude and urgency of this demand are highest in the high-penetration scenario. Where training provision develops slowly, the model projects a temporary increase in the number of workers requiring reskilling. More anticipatory training reduces the duration of this gap and supports movement into transformed or emerging roles. Employment and skills results should nevertheless be interpreted cautiously because they are sensitive to assumptions concerning task exposure, service organization and the continued requirement for human supervision.

4.5 Well-being, Safety and Longer-term Spatial Effects

The model projects a gradual reduction in travel-related stress as automated services become more reliable and familiar. Potential benefits arise from avoiding the effort of driving, parking and navigating, as well as from improved service availability. These effects are stronger for users who currently experience substantial travel constraints. In the short term, the benefits remain limited by uncertainty and low exposure. Some population groups may initially experience additional stress because of concerns about system reliability, lack of control or the absence of a human operator. As positive operational experience accumulates, perceived safety improves and the well-being benefit becomes more pronounced.

The safety effects also increase with penetration. Low adoption produces only a limited system-level change because conventional vehicles continue to account for most traffic exposure. Under the reference and high-penetration scenarios, the potential reduction in accidents and fatalities becomes more visible as automated vehicles account for a larger share of travel. The scale of the effect depends on actual technical performance and the operation of CCAM vehicles within mixed traffic. The model does not assume that every automated journey has no accident risk. Instead, safety improvement is introduced as a scenario-sensitive relationship that varies according to automation level and system exposure.

A feedback relationship is observed between safety and adoption. Improved safety performance strengthens confidence and supports further adoption. Conversely, incidents or technical failures can reduce perceived safety and slow diffusion. This feedback is particularly influential during the early stages, when public attitudes are less established. The residential and spatial effects emerge primarily in the long-term horizon. Private automated vehicles generate the strongest potential for longer-distance travel because users may perceive travel time as less burdensome. This can increase the attractiveness of living farther from employment or services.

Automated taxis and shared services may produce a similar effect, but the outcome depends on pricing and availability over longer distances. Automated buses and shuttles are less directly associated with residential dispersion when they are integrated with public transport and support more concentrated development patterns. The spatial forecasts are more uncertain than the immediate adoption and accessibility results. Residential decisions are influenced by housing markets, land-use policies, employment locations and household preferences that extend beyond the model boundary. They should therefore be interpreted as indications of possible pressure rather than precise relocation forecasts.

5 Conclusions and Next Steps

Deliverable D4.7 developed a social impact assessment model for examining how alternative CCAM deployment pathways may affect different population groups and social outcomes over time. The model advances the impact mapping undertaken in D4.6 by translating stakeholder and citizen evidence into a dynamic, scenario-based forecasting framework. It combines population-group adoption, contextual forecasts and system dynamics relationships to assess effects across the short-, medium- and long-term horizons.

The findings demonstrate that the social consequences of CCAM depend not only on the level of automation or rate of technological penetration, but also on the conditions under which services are introduced. Higher penetration can increase potential accessibility, safety and well-being benefits, but it can also accelerate employment transformation, increase pressure on skills systems and produce uneven outcomes if service coverage and affordability remain limited. Accessibility emerges as one of the principal potential benefits. Automated taxis, buses and on-demand shuttles can improve mobility for non-drivers and people with limited access to conventional transport. Nevertheless, effective accessibility depends on pricing, geographical coverage, accessible vehicle and interface design, and the availability of assistance. Technological availability should therefore not be interpreted automatically as social accessibility.

The results also underline the importance of population heterogeneity. Early adoption is generally stronger among technologically confident users and within areas receiving the first services. Without inclusive deployment conditions, these differences may persist even as overall penetration increases. Aggregate improvements should therefore be examined alongside their distribution across population groups and territories. Employment effects are expected to occur through a combination of task displacement, occupational transformation and the creation of new technical and supervisory roles. Increasing penetration consistently raises the requirement for new skills, although the net employment outcome remains dependent on service organization, automation level and the availability of reskilling.

The forecasts remain subject to important limitations. Large-scale empirical evidence on highly automated mobility remains limited, and several relationships rely on stated preferences, stakeholder expectations and explicit scenario assumptions. The national survey samples also differ in size, while some socially important groups cannot be identified directly in the population data. The results should consequently be interpreted as conditional projections rather than precise predictions.

The next step is the structured assessment of the model and its forecasting results under Task 4.C.4. Deliverable D4.8 will document the involvement of relevant experts, industry actors and stakeholder representatives in reviewing the model structure, assumptions and projected effects. The resulting feedback will support the refinement of model relationships and improve the practical relevance, transparency and reliability of the social impact assessment.

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