International Transport Forum

Skills Move us Forward: Transport Workforce Skills in the Age of AI

Summary and Conclusions

201

Roundtable

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The International Transport Forum

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International Transport Forum
2 rue André Pascal
F-75775 Paris Cedex 16
contact@itf-oecd.org
www.itf-oecd.org

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Executive summary

Main findings

The integration of artificial intelligence (AI) into transport workflows poses a fundamental challenge: ensuring the workforce can adapt while maintaining safety and operational resilience. As AI technologies become ubiquitous, the ability of workers to acquire relevant knowledge, skills and abilities becomes critical. Effective reskilling depends on enabling individuals to develop additional AI-relevant capabilities. Developing skills holds value from both a labour and societal perspective: they enable individuals to adapt to changing working environments and respond effectively to disruption. Skills development also holds intrinsic value beyond immediate workplace application, contributing to individual adaptability and broader societal resilience.

A clear understanding of the skills required in the transport sector is essential to informing skills development strategies. Occupations in the transport sector heavily rely on cognitive and basic skills, reflecting the importance of human judgment in managing complex systems. Strong requirements for communication-related skills (oral comprehension and expression, critical thinking, etc.) emphasise the importance of co-ordination in transport-related occupations. These basic skills form a common capability basis shared across the sector. Physical and psychomotor abilities are moderately relevant as a result of earlier waves of automation (e.g. robotisation). Sensory abilities associated with safety and situation awareness (e.g. vision, attention, hearing) remain particularly important. By contrast, advanced digital and technical skills are less prevalent in the transport sector, indicating that transport expertise builds primarily on operational, cognitive and sensory capabilities rather than specialist technical expertise.

The progressive integration of AI in transport activities is increasing the demand for new skills, including those related to AI. Occupations with high AI exposure will likely demand skills such as management, business processes (e.g. project management, budgeting, accounting, administration) and social skills. Needs for AI-related skills will vary significantly across occupations. While a small number of roles may require extensive and in-depth AI expertise, most occupations will need basic levels of AI awareness, literacy, competency or proficiency to effectively and safely interact with AI-enabled systems.

More importantly, the automatability of certain skills within the transport sector does not eliminate the need for their continued development. In safety-critical applications, maintaining the development of workers' skills, especially cognitive skills, remains essential to managing risks and addressing potential AI system failures. Within safety-critical occupations, public authorities should carefully assess whether AI systems can safely and reliably perform specific tasks compared to human workers before authorising their automation.

While a certain level of skills erosion is expected, erosion of critical expertise in the transport sector should be considered risky if it reduces workers' vigilance. Overreliance on AI may accelerate skills erosion and lead workers to blindly trust AI outputs and adopt its biases and errors (e.g. mis-skilling).

As AI capabilities continue to evolve, public authorities must monitor AI capabilities and take an anticipatory approach to AI governance to ensuring individuals are equipped with the necessary skills. Five guiding principles can steer future skills strategies: that skills development is proportionate to both the transport sector's needs and individual aspirations; that it prioritises the acquisition of enabling and complementary skills; that it retains critical skills and abilities for safety-critical roles and that it accounts for the often invisible and indirect benefits of skills acquisition.

Beyond these guiding principles, public authorities can already act to lower existing barriers to skills acquisition by targeting motivation, capability and opportunity barriers. They can increase motivation by alleviating uncertainty about which skills will be relevant in the future. They can address the motivation barrier by providing education that frames AI as a tool for supporting work rather than a threat, and building partnerships with employers and unions to demonstrate practical use cases where AI unlocks tangible benefits. To reduce capability barriers, public authorities can focus on combining incentivisation with paid training leaves, for example, and enablement measures, such as subsidies or co-funding schemes. This would ease financial burdens associated with retraining. They can also co-ordinate with education and labour market institutions to ensure training programmes are aligned with the sector's evolving needs. Finally, to overcome physical and social opportunity barriers to skills development, including limited physical access to training, public authorities could reshape the training ecosystem by expanding accessible, high-quality and relevant learning opportunities, using digital technologies, including AI. Support should be prioritised for workers most exposed to AI.

Recommendations

Mitigate deskilling and avoid mis-skilling in safety-critical applications

Automation-induced complacency or deferral to AI can reduce transport safety as complacent workers may fail to identify, understand and address automation failures. Overreliance on AI system outputs may gradually erode workers' skills, leading them to "unlearn" previously acquired capabilities. Automation complacency may result in workers blindly trusting AI outputs and adopting its biases and errors (i.e. mis-skilling). While a certain level of deskilling is expected and acceptable to harness the benefits of AI, public authorities should prevent the risks associated with mis-skilling, particularly in safety-critical applications.

Balance skills retention and AI competency

In the face of uncertain AI maturity, skills development strategies must retain critical human skills, particularly enabling skills, which underpin the development of more advanced capabilities. Training programmes should be established before critical skills erode. Skills development strategies should also provide an appropriate level of AI-related competencies, tailored to both the requirements of specific roles and individuals' career aspirations. Achieving this will require strong vertical and horizontal co-ordination among authorities responsible for skills development, spanning primary and secondary education as well as lifelong learning systems.

Recognise and foster non-technical competencies

Skills development strategies should ensure the workforce can acquire non-technical skills that will allow them to work with AI. While some occupations will require AI-related technical skills and knowledge to work on AI models, most workers exposed to AI will not require any technical skills or knowledge relating to how these systems function. Occupations with high AI exposure will likely demand skills that complement AI, such as management, business processes, budgeting, accounting and social skills. These capabilities are critical to unlocking AI's benefits while mitigating its potential risks.

Acknowledge the value of workers learning for the sake of learning, even as AI automates tasks

Public authorities should not underestimate the value of skills acquisition for individuals. There are benefits to learning that extend beyond the acquisition of specific knowledge, specific skills or their use in a specific context. Because a task can be automated does not mean the related skills acquisition is pointless. Skills bear an important societal value for individuals. Certain skills and knowledge can be deployed by individuals beyond the specific context in which they were learned. Learning allows individuals to adapt to their environment and, in turn, shape it. Beyond their important value for employability, knowledge, skills and abilities contribute to the broader resilience of society.

Lower the barriers to skills development

Public authorities should lower barriers to the acquisition of new skills by targeting motivation, capability and opportunity. This includes increasing motivation by framing AI as a supportive tool, demonstrating its practical benefits through partnerships with employers and unions. It also includes addressing capability gaps through incentives like paid training leave and co-funding schemes as well as co-ordinating with education and labour-market institutions to align training with sector needs. Lastly, priority support should be given to workers most exposed to automation by expanding accessible, high-quality digital and AI-enhanced learning.

Introduction

This report is structured around four main sections, guiding the reader from understanding the context in which artificial intelligence (AI) is being deployed in the transport sector to actionable strategies for the transport workforce in the AI age. It has been written to inform policymakers on how to navigate the impacts of AI on the workforce and, more specifically, its effects on skills, abilities and knowledge. The goal is to understand how policy can respond in a way that is proportionate to workers' needs, resilient and forward-looking.

The first section provides foundational background by introducing the key characteristics and capabilities of AI systems. It examines how these intersect with the transport sector, considering both current and emerging workforce-related challenges. This section provides the essential context for interpreting workforce changes and setting priorities for intervention.

The second section of the report shifts from context to analysis. It examines the knowledge, skills and abilities that enable transport systems to function. This section includes a skills inventory, highlighting the most important skills for the transport sector in the context of the progressive deployment of AI systems. It also considers how AI may shape future skills demand.

Based on this analysis, the third section outlines overarching principles to guide future policy and skills development strategies. These principles serve as a strategic compass, highlighting the core values and risks that policymakers should consider when designing interventions.

Finally, the fourth and last section of this report moves from principle to action. While the third section focuses on *why* certain priorities matter, this section focuses on *how* and *what* policymakers can do to address existing barriers to workers' skills development. It suggests practical approaches to enhance workforce readiness by lowering barriers to training. Together, principles and strategies provide a complete framework for policy grounded in both evidence and practical action.

Understanding: AI and transport workforce essentials for policymakers

Advances in artificial intelligence (AI) are reshaping society and labour markets. AI is not only influencing employment levels and job quality, but transforming the nature of work performed by workers and the skills that will be required of them (OECD, 2023). More fundamentally, AI is shifting the locus of transport knowledge away from sector-specific expertise towards the information and communication technologies (ICT) and technology domain. The nature of transport work is placing growing emphasis on the design, engineering and management of algorithms governing transport. Within the transport sector, AI introduces new opportunities as well as complex risks and challenges for the formal and informal transport workforce. As AI takes on a greater role in planning, operations and maintenance, the skills required to manage, interpret and collaborate with these technologies are evolving rapidly. Traditional technical expertise must now be complemented by AI literacy and, more generally, by a functional and ethical understanding of AI-related systems.

Understanding the fundamentals of AI and the transport workforce is essential to anticipate if, where and to what extent the transport workforce will be impacted by AI. This section provides the conceptual ground needed to design effective, forward-looking skills and labour policies.

AI characteristics and capabilities

As AI is increasingly able to acquire skills and perform tasks previously thought to be hard to replicate, its development is associated with changes in skill requirements. In a context where AI is expected to have a growing role in the future of work, understanding the characteristics, scope, development and limits of AI capabilities is crucial to assessing how it may impact the nature of transport sector work and the human skills required to carry it out.

Defining AI

AI can be defined in multiple ways. These definitions are often categorised as technology-based (i.e. what AI is), functionality-based (i.e. what AI does) and outcomes-based (i.e. what AI can achieve).

The International Organization for Standardization (ISO) defines AI as "a machine or computer system's ability to perform tasks that would typically require human intelligence. It involves programming systems to analyse data, learn from experiences, and make smart decisions – guided by human input" (ISO, n.d.).

The OECD expands that view by describing AI systems as being designed to pursue "explicit or implicit objectives and infer from the input they receive how to generate outputs such as predictions, content, recommendations or decisions that can influence physical or virtual environments. Different AI systems vary in their levels of autonomy and adaptiveness after deployment" Click or tap here to enter text..

These definitions highlight several important aspects of AI systems:

AI is a machine-based system

AI systems are complex hybrid technologies that combine physical (e.g. infrastructure supporting AI, data centres, hardware) and virtual elements (e.g. algorithms, data) (European Commission, 2024).

AI systems perform tasks that would normally require human intelligence

They can replicate or simulate cognitive functions, such as perception, reasoning, learning, problem-solving, inferring and decision making. For example, natural language processing models allow AI systems to process and generate human language, a capability that would traditionally require human linguistic skills. Likewise, computer vision systems can interpret visual information, such as video from security or traffic cameras at intersections, and draw conclusions, tasks traditionally handled by trained professionals (e.g. road traffic managers).

AI operates with varying levels of autonomy

This may, in turn, influence the degree of human involvement required in AI operation or in the decision-making process. These levels range from "Human out of the loop", where the AI system operates autonomously by producing a decision outcome and acting on it, to "AI in the [human] loop", where the AI system provides input to a human-led decision process. ITF (2025a) outlines a more comprehensive set of possible human-AI combination types. For example, while automated vehicles display higher automation levels by responding to dynamic traffic conditions, their operation may need to be supervised by a safety driver, which illustrates a "human on the [AI] loop" set-up, where the human monitors the AI system's performance and intervenes if necessary.

AI operates based on predefined objectives to guide its actions

AI systems are developed to achieve explicitly or implicitly defined objectives (Naillat, 2025). Automated vehicles (AVs) make real-time driving decisions under predefined objectives. These may include following traffic rules, driving below speed limits, ensuring the safety of other road users and passengers and optimising energy use. These rules must be determined and encoded by humans, often requiring the translation of abstract and implicit principles (e.g. drive safely) into a machine-readable format to be processed by AI systems (ITF, 2019, 2024). AI systems may self-define implicit sub-objectives, allowing them to achieve their final objective. These sub-objectives may prove problematic.

AI must be trained to acquire skills

AI systems require extensive training data to develop the skills to perform specific tasks effectively. AI systems rely extensively on human-generated data (i.e. text, images, statistical records) (Peukert et al., 2024). Human behaviour plays a central role in shaping AI training. AI system developers actively develop or select datasets for training based on technical objectives they feel are relevant. Conversely, humans can influence AI systems' training by deciding what not to train the AI system with by restricting access to certain content (e.g. copyright material, culturally sensitive or biased datasets). In other words, AI systems' knowledge and skills are, to some extent, the result of human decisions.

AI systems can have tangible impacts on virtual and physical environments

The outputs generated by an AI system (e.g. predictions, content, recommendations, decisions) can produce tangible effects in both the real world (i.e. physical environment) and in digital spaces (i.e. virtual environment). In the physical world, an AI system embedded in automated vehicles directly influences the vehicle's behaviour. It will determine how the vehicle accelerates, brakes or navigates. These decisions not only affect the individual vehicle, but also broader road safety performance and traffic patterns. On the other hand, in the virtual environment, AI-based trip planning tools can shape user experience and access to information by generating tailored travel recommendations based on several factors (e.g. personal preferences, historical data and real-time transport conditions).

AI systems may evolve after deployment

Unlike traditional ICT systems, which behave consistently unless explicitly updated, many AI systems are designed to evolve over time. Their performance may change post-deployment through self-learning after being exposed to new collected data (Naillat, 2025). Ensuring AI systems' reliability after they are deployed is crucial. Human oversight, through post-deployment monitoring, auditing and performance evaluation, ensures that AI system adaptation does not lead to a deviation from their intended objectives, expected results, and, more generally, societal values. These deviations can have critical and high-risk consequences within the transport sector (ITF, 2025a). The performance of an AI system optimised to maximise transport revenues may learn that certain trips contribute disproportionately to revenue and, in turn, decide to favour those to the detriment of other less profitable trips.

Characterising AI: Types, methods and capabilities

The AI landscape is not uniform. The term AI covers a broad range of technologies from machine learning to hybrid learning to generative artificial intelligence. Misunderstandings can arise when approaching it as a singular or monolithic technology. It is more accurate to speak about AI technologies or systems to reflect the diversity of AI. AI applications can be classified depending on the type of technology used, the methods on which they rely, their level of criticality or their capabilities (European Commission, 2024; Republic of Korea, 2025; Schmid et al., 2021).

AI systems rely on a broad range of underlying algorithmic methods. Click or tap here to enter text. provides a comprehensive overview of the different technical foundations and methods on which AI systems rely. For example, machine learning models may adopt different learning paradigms between supervised learning (i.e. the model learns from labelled input/output pairs), unsupervised learning (i.e. no labels provided, the model finds structure in the data) and reinforcement learning (i.e. the model learns by interacting with the environment to maximise rewards). AI models may also vary in classification techniques used between rule-based methods, machine-learning-based methods, deep learning-based methods and hybrid methods .

Additionally, several AI regulatory frameworks have adopted risk-based classifications of AI systems . The central principle of such an approach is that AI should be governed not by what *it is* (e.g. method, capability, underlying technology), but by what *it does* and the risks it creates. Regulation is thus tied to the system's potential impact and not the system's characteristics. For example, the EU's AI Act differentiates four levels of risks related to AI systems: no or minimal risk, limited risk, high risk and unacceptable risk. Systems posing minimal or no risk are subject to no specific obligations, while those classified as limited or high risk must comply with increasingly stringent transparency, safety and accountability requirements. AI systems presenting unacceptable risks, i.e. contradicting EU values, laws or fundamental rights, are prohibited.

Finally, AI systems can be distinguished by the capabilities they exhibit, many of which have been inspired by human capabilities Click or tap here to enter text.. However, currently deployed narrow AI systems only enable a subset of human capabilities. Narrow AI systems are trained to perform specific tasks or a set of closely related tasks with a high level of accuracy and efficiency (e.g. crash detection systems, demand forecasting, traffic monitoring). Different narrow AI systems will be required to perform different sets of tasks that would normally rely on different human capabilities. Comparing AI systems' capabilities to human capabilities and monitoring their evolution is a starting point to understand AI's potential to replace or augment human task performance (OECD, 2025c). Analysis conducted by the OECD (2025c) assessed and compared AI systems' capabilities against human abilities on a scale from 1, which reflects solving AI problems in the different categories, to 5, which reflects performance that fully simulates the range of corresponding human abilities (Table 1). They provide policymakers with an evidence-based framework to evaluate AI's progress and to design education and workforce policies that reflect this evolving relationship.

Table 1. OECD artificial intelligence capability indicators and current capabilities

Domain	Level (from 1 to 5)	Summary of level capability description
Language	3	AI systems at this level reliably understand and generate semantic meaning using multi-corpus knowledge. They show advanced logical and social reasoning ability and can process text, speech and images. They support a diverse range of languages and adapt through iterative learning techniques.
Social interaction	2	AI systems combine simple movements to express emotions and learn from interactions for future encounters. They recall events and adapt slightly based on experience, recognising basic signals and detecting emotions through tone and context. They also perceive individual distinctions and apply past experiences to recurring challenges.
Problem solving	2	AI systems integrate qualitative reasoning – such as spatial or temporal relationships – with quantitative analysis to address complex professional problems framed using conventional domain abstractions. They handle multiple qualitative states and transitions, predicting how systems may evolve or change over time.
Creativity	3	AI systems generate valuable outputs that deviate significantly from their training data and challenge traditional boundaries. They generalise skills to new tasks and integrate ideas across domains.
Metacognition and critical thinking	2	AI systems monitor their own understanding and adjust their approaches accordingly. They work with familiar information that may contain ambiguities, requiring measured confidence and informed guesses. They can handle partially incomplete information by discerning what they know and what they do not.
Knowledge, learning and memory	3	AI systems learn the semantics of information through distributed representations and generalise to novel situations. They can process massive datasets for context-sensitive understanding, but lack real-time learning capabilities.
Vision	3	AI systems can handle some variation in target object appearance and lighting, perform multiple sub-tasks and can cope with known variations in data and situations.
Manipulation	2	AI systems handle a variety of object shapes and moderately pliable materials, operating in controlled environments with low to moderate clutter. They navigate around small obstacles in open spaces, accommodate objects placed randomly within a defined region and perform tasks without time constraints.
Robotic intelligence	2	Robotic systems operate in partially known, mostly static, semi-structured environments with some well-defined variability. They handle short-horizon, simple, multi-function tasks that, while well defined, involve inherent uncertainty. They can engage in limited human interaction, such as minimal interfaces, and manage some unexpected outcomes within familiar task settings. They deal with little to no ethical issues.

Source: ITF (2025a) based on OECD (2025c)

The transformative power of AI

The uptake of AI is underpinned by progress in three key areas: the exponential growth in data availability to train AI models, continuous algorithmic improvements and the rapid expansion of computational resources (i.e. central processing units, graphical processing units, data centres). These factors contribute to accelerating AI capabilities. Artificial intelligence enables machines to perceive, learn, interpret and act. While some models are focused on discrete tasks (i.e. pattern identification, data analysis), developments in Generative AI (GenAI) in recent years are broadening AI's potential applications (Cazzaniga et al., 2024).

With GenAI, AI is evolving towards a general-purpose technology (GPT)⍰.GPTs are described as platform technologies with multiple applications across several industries (i.e.steam engine, electricity, etc.). GPTs share several characteristics Click or tap here to enter text.⍰:

- Pervasiveness: a GPT has multiple applications and is widespread in the economy.
- Improvement: a GPT is technologically dynamic and will experience efficiency improvement throughout its lifetime Click or tap here to enter text.
- Innovation complementarity: a GPT enables new ideas, products, applications or services to emerge Click or tap here to enter text.

Like other GPTs, AI is transforming the sectors to which it is applied Click or tap here to enter text.. In the transport sector, AI is propelling innovation and impacting the entire transport value chain. AI-powered applications are already operational or under development. Computer-vision systems enable more efficient data extractions from already installed cameras; AI can improve the extraction of items from large datasets collected by public authorities; AI models can be used for fleet and traffic management, and automated vehicles. These applications support more efficient management and contribute to the efficiency of the system as a whole Click or tap here to enter text.. AI's rapid uptake in transport workflows is impacting a broad range of human activities, leading to a loss of interest in certain human skills without yet knowing what the ultimate performance of AI systems will be.

The direction and extent of transformations enabled by AI do not follow predetermined paths. It is contingent on other decisions, changes and events. AI deployments interact with socio-cultural values and existing institutions. At the same time, positive or harmful events can steer the AI adoption pathway in one way or another. In this context, the role of policymakers is to anticipate and address unforeseen consequences of societal changes introduced by AI and to govern such shifts to ensure they are equitable and beneficial for the population (The British Academy, 2025).

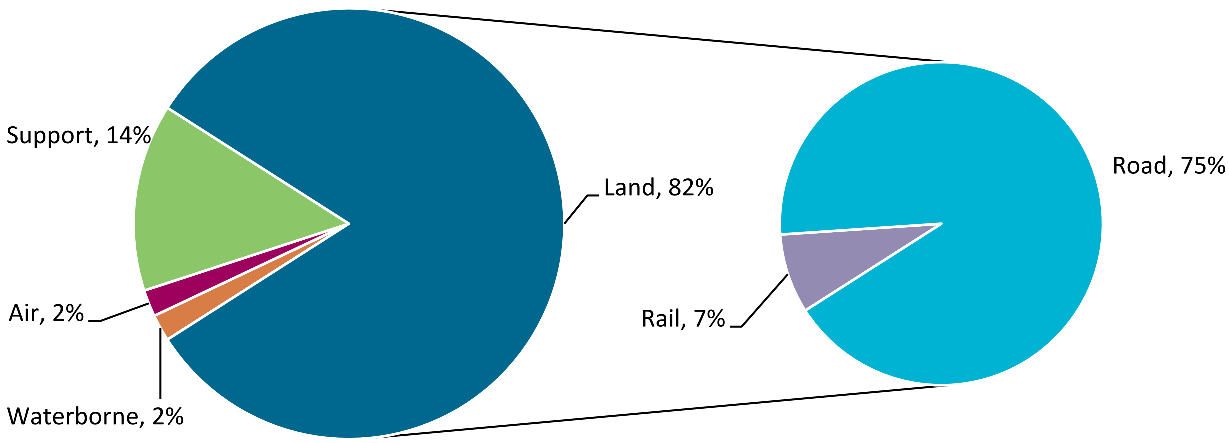
The transport workforce in the AI age: Challenges and prospects

The transport sector plays a vital job-enabling role across the wider economy. Challenges affecting its workforce can have ripple effects well beyond the transport sector itself. Labour or skills shortages within the transport sector may impact other industries, such as tourism, construction, services or retail. Understanding the challenges facing the transport workforce and the potential impact of emerging technologies, such as AI, is essential for understanding how AI may reshape roles and skills in the transport sector. In addition, transport work is performed across both formal and informal labour arrangements, with the informal workforce often facing distinct challenges and vulnerabilities. While these dynamics are equally important, this analysis focuses on the formal transport workforce, where AI adoption tends to be more advanced and skills implications more clearly observed.

Size and structure of the transport workforce

The transport sector is a major employer. In Europe, approximately 6.2 million people were employed in the transport sector in 2023, accounting for 3.1% of total EU employment Click or tap here to enter text.. In the United States, the "transportation and warehousing sector" represented 16.2 million persons in 2024 (10.3% of the total U.S. workforce) Click or tap here to enter text.. The transport workforce is distributed across a variety of domains, including land, air, waterborne and support occupations. Within this, the road sector represents the largest share of workers (Figure 1). However, the distribution of transport employment can vary significantly depending on the structure of the economy, and physical and infrastructural characteristics. Accurately assessing the total transport workforce remains challenging both in quantitative terms (i.e. number of workers) and qualitative terms (i.e. types of jobs) due to the complexity and diversity of transport activities as well as persistent methodological and data collection limitations.

Figure 1. Global employment distribution across the transport sector by mode



Source: World Maritime University (2019)

Box 1. The challenges of assessing the transport labour ecosystem

Most existing estimates of total employment in the transport sector tend to adopt either a sectoral (i.e. road transport, maritime, aviation) or geographical perspective (i.e. European Union, United States) (Eurostat, 2022; UITP, 2025; U.S. Department of Transportation, n.d.; World Maritime University, 2019). However, cross-country comparisons are often limited by differences in scope, definitions and methodologies used to measure the transport workforce. These inconsistencies highlight the need for more harmonised data collection to allow for more accurate and comprehensive assessment of the transport workforce.

The distribution of transport employment varies significantly between transport modes and across regions, depending on the geographical and economic characteristics of each region. Some regions with major ports, logistics hubs or dense urban transport networks report substantially higher employment rates in transport-related roles, while others, particularly rural or less connected areas, rely less heavily on the sector for jobs. In the European Union, for example, the transport sector employed 6.2 million people in 2022. On average, land transport represented the largest share of workers, with 89.6% of workers. Yet, this average masks significant regional disparities. For example, air and water transport workforces represented a significantly higher share of total transport employment in Malta (53.6%) (Eurostat, 2022).

To gain a more comprehensive understanding of the total transport workforce, it is also crucial to consider the informal workers supporting popular transport services (ITF, 2025b), which often falls outside official statistics. A significant share of transport services in regions like Asia and Africa is provided through informal systems. Yet, these services still rely on the skills and labour of a wide range of transport workers.

Finally, the care economy constitutes an important, yet often statistically invisible or hidden, productive contribution to the transport ecosystem. Care-related transport could be impacted both from a planning (i.e. routing tools, schedule adjustments) and operational side (i.e. identification of irregular or dangerous operation patterns). In most countries, care work is highly gendered, with women disproportionately bearing these responsibilities in most countries. This form of informal, care-driven labour extends beyond household tasks to also include, in some cases, voluntary community-based services (e.g. community transport). In rural areas, where residents have fewer transport options to meet their travel needs, reliance on small-scale and non-profit community services, supported by volunteer workers, is higher (Ravensbergen and Schwanen, 2024). Although these forms of labour are not always reflected in official statistics, they play a critical role in our societies, sustaining social participation and access to essential services.

Source: (Eurostat, 2022; ITF, 2025b; ITF Global, 2024; Ravensbergen and Schwanen, 2024; UITP, 2025; U.S. Department of Transportation, n.d.; World Maritime University, 2019)

What are the barriers to AI adoption in the transport sector?

Barriers to the deployment of AI in the transport sector can be broadly grouped into technical, organisational, socio-economic and environmental categories. Each group encompasses distinct but interconnected challenges that will influence the pace and scale of AI adoption (Martin et al., 2025).

Technical barriers:

- Data discoverability, ownership/control and quality: Fragmented, low-quality and often inaccessible data can limit the deployment of AI applications.
- Infrastructure for AI integration: Outdated legacy infrastructure is often incompatible with the requirements of modern AI technologies, slowing down AI adoption and scaling.

Organisational barriers:

- Regulation and governance: The rapid development of AI often outpaces regulatory adaptation. Outdated or fragmented regulatory frameworks can make AI deployment complex, while overly stringent regulations may stifle innovation.
- Skills and workforce awareness and readiness: The lack of AI literacy (i.e. to be able to work <u>with</u> AI), expertise (i.e. to work <u>on</u> AI) and awareness of how AI could be used in the transport sector may hinder the capacity of stakeholders to adopt AI. While external expertise can bridge this gap in the short term, long-term reliance on it can reduce profitability and resilience.
- Decision making and accountability: Unclear responsibility for validating AI decisions and addressing errors creates significant governance challenges. The absence of a transparent and well-communicated framework for accountability can hinder AI development at scale.

Socio-economic and environmental barriers:

- Safety, public trust and social acceptance: AI systems in the transport sector must demonstrate reliability and safety to maintain public confidence and uphold the credibility of public authorities.
- Cost to implement and operate with AI: Deploying and running AI solutions requires substantial investment in infrastructure, technology and workforce development. It may also necessitate updating procurement practices and working processes to accommodate new types of systems and services. AI uptake may be slowed by organisational inertia as early adopters must accept and absorb the risks and costs of a “try-fail-learn-repeat” phase, while broader adoption will typically follow once applications deployed are documented enough and have already proven their value.
- Environmental impacts: AI systems, particularly those performing complex tasks, such as automated driving, can be highly resource-intensive, consuming significant amounts of electricity and water.

While some of these barriers can and should be addressed by organisations, others are necessary safeguards that protect essential public interests. Public authorities therefore have a crucial role to play in striking this balance by removing barriers that impede progress in AI, while preserving those that uphold accountability, ensure safety, and protect public interests and values, such as human autonomy. This balance is particularly critical in the transport sector, where failures can lead to serious consequences. Transport authorities should also assess whether AI is the most suitable tool for addressing the problem they aim to solve. While AI may offer one possible solution, it should be assessed alongside alternative and, potentially, non-AI solutions. The adoption of AI systems should be clearly justified by the challenge at hand and its outcomesdemonstrably beneficial (ITF, 2025a).

Transport workforce challenges and how AI is impacting them

The broad applications of AI will transform work and labour (McAfee, 2024). The degree of transformation in transport will be contingent upon the pace of development in AI capabilities in the transport sector as well as a range of non-technological factors, including public acceptance, demographic dynamics and labour costs (National Academies of Sciences, 2024). AI impacts work and labour in the transport sector at different levels:

- Sector level (macro): AI changes the composition of the transport workforce (ITF, 2023; OECD, 2021). AI's impact on the workforce is complex. It is expected to impact the workforce in three main ways: by automating certain tasks and thus displacing certain jobs (i.e. automation); by transforming existing jobs through the integration of AI (i.e. augmentation); by creating new roles, particularly in AI management and supervision tasks (i.e. creation). Yet, the technological dynamism and progressive deployment of AI in the transport sector preclude a definitive assessment of AI's impacts on the workforce (National Academies of Sciences, 2024).
- Occupation level (meso): AI changes the nature and quality of work in transport occupations (ITF, 2023). AI is expected to improve the occupational health and safety of workers by reducing routine or hazardous tasks. At the same time, AI will change working interactions between workers, machines and customers. This may result in changes in terms of work intensity, stress levels and workers' autonomy (Milanez, Lemmens and Ruggiu, 2025; Rani, Pesole and Gonzalez Vazquez, 2024).
- Task level (micro): AI is reshaping the skills and knowledge required to perform specific tasks in transport sector jobs. As AI systems' capabilities continue to expand, the value of certain skills may erode (National Academies of Sciences, 2024). At the same time, the emergence of AI-powered applications is expected to generate opportunities for new tasks and increase the demand for particular skills (e.g. data literacy, critical thinking), thereby shifting skill demand.

Macro: Labour shortages, ageing workforce and changes in the composition of the workforce

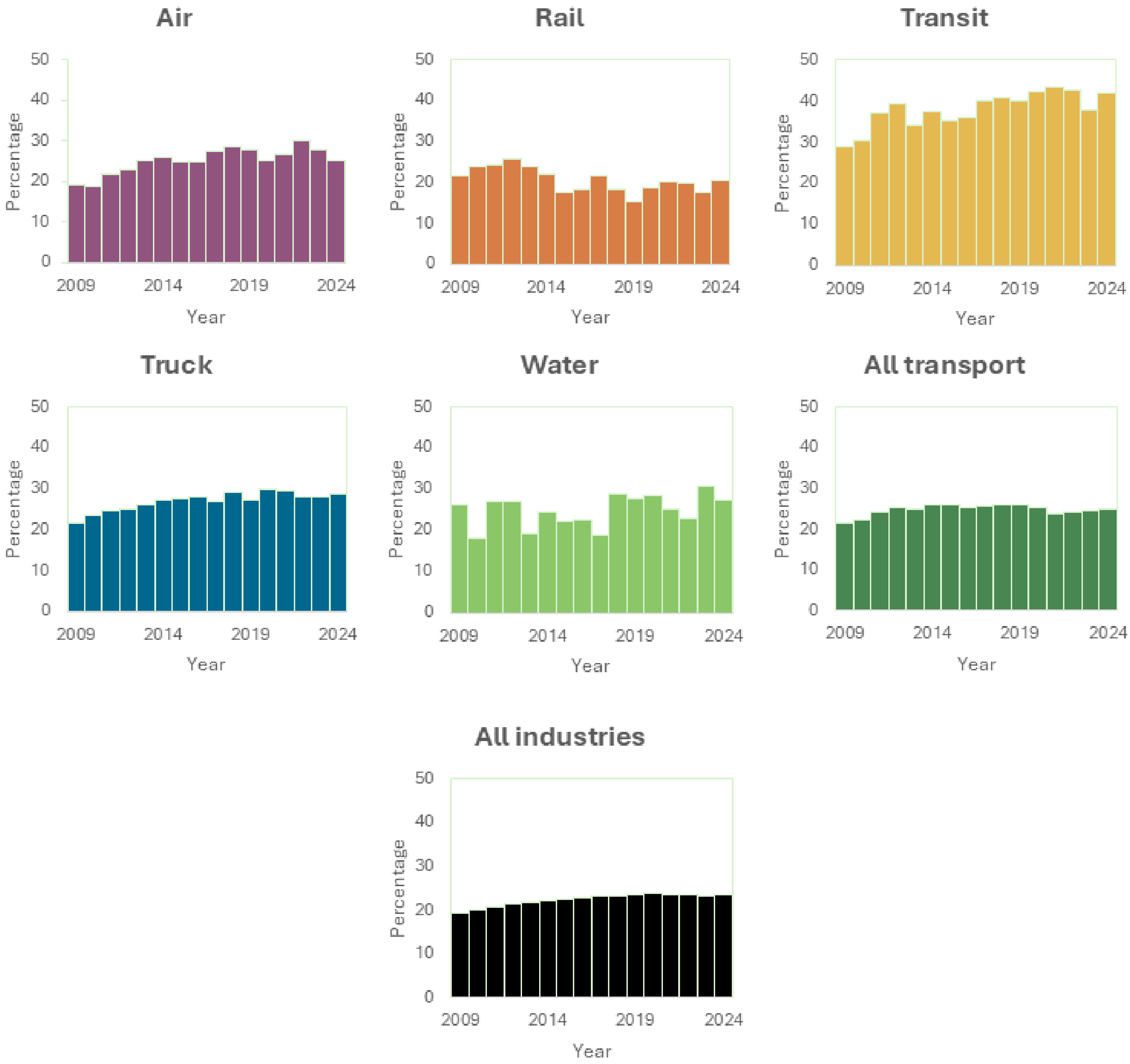
The transport sector faces chronic and structural labour shortages in many countries (ITF, 2023). Labour shortages occur when the demand for labour in certain positions or sub-sectors outpaces the supply of skills. They can be measured across three main factors (CEDEFOP, 2025):

- Demand: Measures the pressure generated by employment growth. High-growth occupations may experience difficulties in attracting workers with the right skills and knowledge.
- Supply: Measures the pressure related to the availability of workers, including replacement needs due to labour market exits (e.g. retirement or career changes).
- Imbalances: At the occupation-level, capture mismatches between the skills supplied by workers and those required by employers. The under- or overqualification of workers may create mismatches between supply and demand, which can contribute to lower workers' satisfaction and productivity.

In OECD countries, labour shortages in the transport sector are rising as a consequence of workforce ageing, with a high proportion of workers aged 55 and above (Figure 2). This trend, which holds across the wider economy, stems from broader demographic shifts, such as declining fertility rates and increased life expectancy, which lead to an overall shift in the population structure (De Gobbi et al., 2025). This phenomenon tends to be more acute in some sectors (e.g. public transport in the United States) (Figure

2). Workforce ageing, combined with the overall sector's persistent difficulty in attracting and retaining younger workers, and the maintenance of current retirement ages, increase the risk of worker shortages. Transport also faces competition from other sectors when it comes to skills that can be transferable from one sector to another, particularly those related to new technologies (e.g. data analytics), including AI.

Figure 2. Percentage of workers aged 55 and over in the U.S. transport workforce, 2009-24



Source: U.S. Department of Transportation (2024)

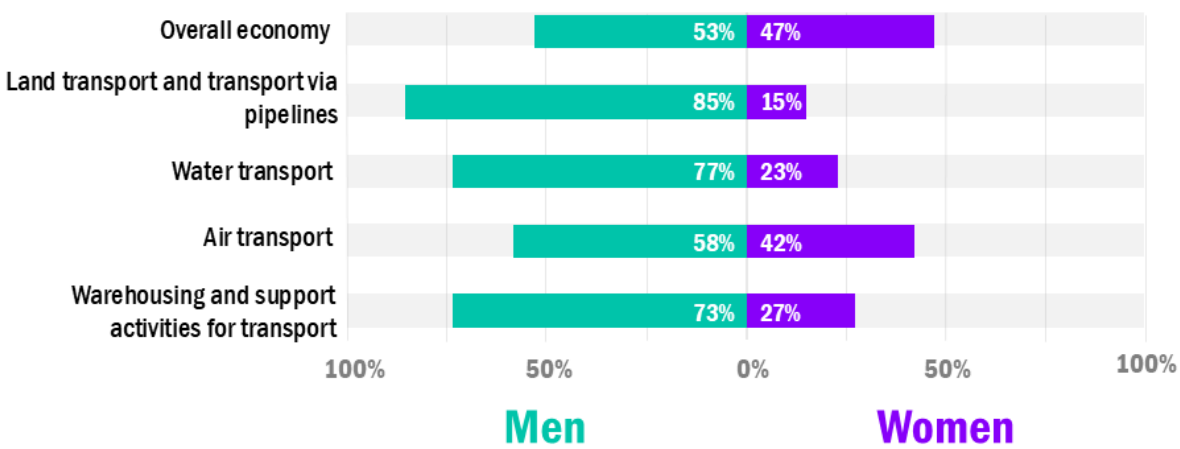
Regulatory requirements may also limit (younger) workers' ability to enter the transport labour market. For occupations that face critical labour shortages, such as truck driving, this may discourage new and younger entrants from entering the profession. However, as noted by Baranska and Picard (2023), labour shortages, defined as situations in which demand for workers willing to work under specific conditions and possessing the required skills for the occupations exceeds the available supply of workers, are typically characterised by high vacancy rates (i.e. share of vacancies among all jobs). Importantly, such vacancies may stem from multiple factors, including unattractive working conditions. Solutions to alleviate these barriers could include increasing training capacity, creating more flexible training programmes and covering licence costs, for example. At the same time, measures should also address the underlying causes of job unattractiveness, when relevant.

From a labour perspective, the introduction and adoption of new technologies in the transport sector could bring significant opportunities to mitigate the ageing impact on worker shortages. AI may be applied to address tasks that are characterised by important labour or skill shortages (ITF, 2023). By taking on repetitive, physically demanding or high-risk tasks in areas that are lacking workforce, AI can help alleviate labour shortages. For example, the automation of driving-related tasks and manoeuvres with automated vehicles (AVs) could be expected to reduce tension on workers and ensure continuity of the transport service. At the same time, the deployment of automated vehicles will generate demand for new categories of skilled workers to oversee Society of Automotive Engineers (SAE) level 3-4 AV operations, including safety and remote drivers. Although fully autonomous vehicles (SAE level 5) would eliminate the need for an onboard driver, this absence would need to be offset by complementary support and skilled roles, such as transport assistance and safety agents. While AV's ancillary support roles (e.g. maintenance, recovery, cleaning) might be less exposed to AI, they remain highly vulnerable to the negative impacts associated with sub-contracting, including inadequate working conditions (DARES, 2011).

Macro-meso: How changes in the nature of work may impact transport workforce gender imbalance

According to ILO (2023), women only represent 12% of the transport workforce globally. However, this imbalance differs both regionally (e.g. 21% in Germany against 3% in Albania) and depending on the sub-sector considered (Figure 3). Additionally, distribution of roles is highly gendered within the transport sector, where the proportion of women is higher in service-oriented or administrative activities (ETF, 2020; World Bank, 2025). On the contrary, women's participation is lower in technical roles across all skill levels.

Figure 3. Gender distribution of jobs in the transport sector in the EU



Source: (Eurostat, 2024a)

Note: The data include workers aged between 15 and 64 in the 27 European Union countries. It does not include informal workers.

Against this backdrop of gendered imbalance, working conditions, particularly in terms of flexibility, play a critical role in shaping women's participation in the transport sector. Digital technologies, including AI, present both opportunities and challenges in shaping more flexible work arrangements (Jain and Kanwar, 2025). AI-powered automation could improve work-life balance by allowing for more flexible working hours and remote work (European Commission DG Mobility and Transport, 2021). Flexibility is essential for improving working conditions and supporting the participation of underrepresented groups, particularly women, in the transport labour market (ITF, 2023). As noted by Turnbull (2013), the road sector is particularly unappealing to women due to fixed and often demanding working hours and extended periods away from home. AI could positively impact temporal and geographical flexibility (Jain and Kanwar, 2025). From a temporal perspective, the deployment of AI-driven asynchronous collaboration tools (i.e. project management software, communication platforms, etc.) can improve asynchronous work arrangements. From a geographical perspective, AI-powered communications technologies can reduce geographical constraints on work. Smart scheduling systems can support more flexible working arrangements.

Flexibility should be primarily targeted towards the worker. A worker-centred approach to flexibility ensures that technologies, including AI, serve the needs of the worker. However, flexible work arrangements enabled by AI can also lead to an increase in work pressure and pose health risks (e.g. stress, anxiety, psychosocial and physical problems), and ultimately reduce workers' autonomy (Eurofound, 2020). Examples can be found among app-based delivery services workers. While algorithmic management systems, which determine task allocation (in both space and time), performance rating, and pay, offer nominal flexibility, they tend to incentivise long working periods, rapid task completion and unsafe behaviour through dynamic pricing and performance-based penalties. In this context, if flexibility is targeted towards the needs of the business and customers, it could potentially undermine job quality and safety. Alauddin et al. (2025) note that gig workers' lack of necessary skills or knowledge can undermine flexibility and have adverse effects on their mental health.

Micro: Impact of AI on skills

AI is not knowledge- or skill-neutral: it will affect certain tasks more than others (ITF, 2023). AI is expected to impact the supply of skills and knowledge in the transport sector in different ways by:

- Reducing skills shortages when AI replaces human input in tasks where there is currently an underprovision of skilled workers
- Reinforcing skills surpluses when AI replaces human input in tasks where there is currently an overprovision of skilled workers (e.g. low-educated and physical skills)

Beyond substitution effects, AI is also expected to create new demand for AI-related skills and reinforce the demand for so-called bottleneck skills that remain difficult to automate (e.g. cognitive, social skills, critical thinking, etc.) as these become more central to task performance once routine activities are automated. Approaching AI impacts through the lens of their effects on skills rather than entire occupations allows for a more precise understanding of which skills will be most exposed to AI (i.e. automatable). Most jobs rely on a combination of automatable and bottleneck skills (Lassébie and Quitini, 2022).

Mapping skills with higher exposure to AI will thus be essential to target training activities. The following sections will explore the relationship between AI, skills and knowledge. It will examine the role skills play in the transport sector and how they are going to be impacted by AI. It will then look at principles to ensure skills acquisition strategies can help workers adapt to a more automated transport sector, while ensuring skills provision is adapted and proportionate.

Mapping: Skills for the transport workforce in the AI age

As AI and, more generally, digital technologies become more prevalent in transport activities, the ease with which workers acquire the necessary knowledge and skills to work with these tools becomes a critical factor in ensuring service continuity. While this adaptation represents a considerable challenge, evidence suggests it is achievable (National Academies of Sciences, 2024). Public authorities can steer skills acquisition through targeted strategies (e.g. training, certificate programmes) and education policies to balance the provision of knowledge and skills within the transport sector and assist existing or future workers in adapting to the transition to an automated labour market.

Continuous and updated lifelong education and skills acquisition strategies are crucial to harness AI benefits, as is the case with other GPTs (Jovanovic and Rousseau, 2005). The transport sector is going through a phase of AI experimentation where stakeholders explore different approaches at different speeds and scales of deployment to seize opportunities opened by AI (Laino, 2019). During this phase, uncertainties regarding the technology's capabilities and skills requirements can arise, illustrating what Laino (2019) describes as a time gap between introducing technology and acquiring the necessary skills to harness AI benefits.

Future skills strategies for the transport sector should begin with a comprehensive inventory of the current skill supply, an assessment of how exogenous factors, such as AI, will impact this supply, and an evaluation of future skills demand. This initial assessment provides evidence needed to design effective skills strategies, and implement policies and actions to equip individuals with the right skills to adapt to the changes introduced by AI.

Knowledge, skills, abilities, tasks: Why they matter

It is essential to clarify what is meant by knowledge, skills, abilities and tasks. These terms, though often used interchangeably, describe different dimensions of work. Distinguishing these concepts provides a common lexicon to understand what workers need to know and do for a given occupation. It ensures that assessments of the skill supply are accurate, coherent and aligned with the sector's real functional needs.

From knowledge to action: How knowledge, skills and abilities shape tasks

Knowledge, skills, abilities and tasks are the essential building blocks for achieving an occupation's objectives. They define what people know, how they can act and what they actually do. Knowledge, skills and abilities, and tasks are connected in a local sequence: knowledge forms the conceptual foundation, skills and abilities translate that knowledge into an actionable capacity, which is then expressed in the performance of tasks (NIST, 2021).

More specifically:

- Knowledge refers to the set of concepts and principles that individuals retain and can retrieve. Knowledge describes what individuals "*know*" and forms a conceptual foundation on which skills and abilities are built, providing the content and context necessary for effective action. For example, bus drivers must be familiar with traffic rules and regulations to perform their duties safely. Knowledge can also be reflexive (i.e. awareness of what one knows), a characteristic that remains essentially human.

- Skills and abilities describe the capacities that enable individuals to perform a task. They refer to what individuals "*can do*". Skills translate knowledge into a practical capability. They can be basic, digital, social, technical, etc. Abilities refer to individuals' attributes that can influence their performance. They can be cognitive, physical, sensory or psychomotor. Supported by knowledge, skills and abilities can be applied to real-world contexts. For a bus driver, operating a bus safely relies on several skills and abilities, such as co-ordination, reaction time, situational awareness and others.
- Tasks refer to the observable actions performed as part of an occupation. They describe the application of knowledge, skills and abilities to real-world contexts; in other words, what "*must be done*" as part of a job. For a bus driver, tasks would include driving along assigned routes, stopping safely at bus stops, assisting passengers and responding to unexpected events or road conditions.

Skill levels in the transport sector

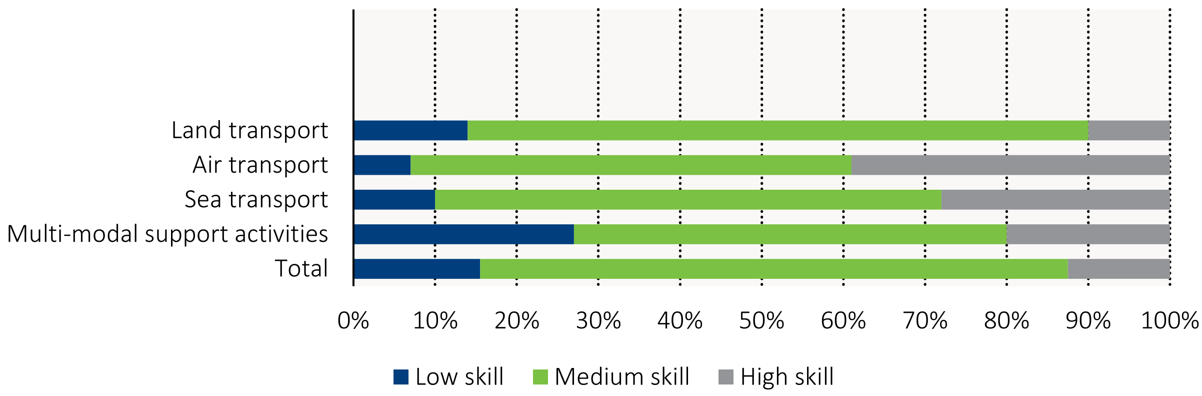
Each occupation requires a distinctive set of skills at different skill levels. ILO (2012) defines skill level as "*a function of the complexity and range of tasks and duties to be performed in an occupation*". It considers the nature of work, the level of formal education required to perform the job and the amount of experience or informal on-the-job training required to perform the tasks related to the occupation.

Occupations can be grouped into different families (ILO, 2012; World Maritime University, 2019). This report will consider low-skill, medium-skill and high-skill occupations:

- A low-skill job refers to an occupation that involves the performance of routine physical, simple or manual tasks. Many low-skill occupations require physical strength and endurance. It corresponds to Skill Level 1 in the International Standard Classification of Occupations (ISCO-08) skill levels. Within the transport sector, it corresponds to occupations such as dock workers, freight handlers, etc.
- A medium-skill job involves the operation of technical or electronic equipment, the maintenance of such equipment, driving vehicles, etc. This job category requires advanced literacy and numeracy skills, and communication skills, along with the knowledge generally acquired through secondary education. Medium-skill jobs correspond to Skill Level 2 in ISCO-08 skill levels. In the transport sector, it corresponds to occupations such as drivers, passenger attendants, motor vehicle mechanics, etc.
- A high-skill job involves the performance of tasks requiring technical and complex decision-making and problem-solving skills. Occupations in this category also require an extensive knowledge base, with high levels of literacy and numeracy skills. High-skill occupations typically require advanced knowledge and specialised skills, often acquired through tertiary education. On-the-job training and experience may also serve as substitutes for formal education. High-skill jobs correspond to Skill Levels 3 and 4 in ISCO-08 skill levels. Within the transport sector, it corresponds to occupations such as transport planner, airline pilot, ship or traffic engineer, etc.

An analysis of workers by skill level shows that the transport sector relies heavily on middle-skilled jobs (i.e. ISCO-08 Level 2). A modal breakdown analysis shows the distribution of skills is uneven across the transport sector (Figure 4. Global distribution of workers by skills and domains, depending on the domain (i.e. land, air, waterborne transport) and type of occupation (i.e. management, maintenance, operation, planning) considered. Land transport tends to rely more on medium-skill occupations, such as drivers or machine operators. Air transport accounts for a larger share of high-skill jobs, including airline pilots. Low-skilled occupations tend to be more represented in multi-modal support activities, which include physical and routine occupations, such as freight handlers, warehouse workers, etc.

Figure 4. Global distribution of workers by skills and domains



Source: World Maritime University (2019)

Skills development is a critical driver of productivity and economic growth. In contexts where the working-age population is declining, strengthening individual workers' skills becomes increasingly important to sustain economic growth (OECD, 2019a). In the transport sector, targeted skills development can improve labour productivity (i.e. total output per hour worked) and help offset the decline of labour utilisation (i.e. ratio of time worked per capita) by enabling workers to adapt to technological change, including AI.

Nature of tasks in the transport sector

The transport sector is a complex socio-technical system. Within such a system, tasks range from highly routine to more complex, judgment-based and cognitively demanding activities. The introduction of automation and AI has been reshaping how these tasks are performed.

Both humans and automated systems have relative strengths and limitations. The convergence of human and automated system capabilities raises fundamental questions: when, where and how much automated systems and humans should be involved in tasks (Cummings, 2014):

- When: This refers to the conditions under which humans or automated systems are engaged in the task;
- Where: This concerns the stage of the task performance pipeline at which human or automated systems are engaged (i.e. planning, co-ordinating, acting, monitoring);
- How much: This refers to the degree of human and automated systems involvement in task execution and the allocation of responsibility between them. The level of engagement can vary along a spectrum from continuous involvement (i.e. human-in-the-loop) to supervisory oversight (i.e. human-on-the-loop) to exceptional engagement (i.e. human-out-of-the-loop).

Clarifying *when*, *where* and *how much* human and automated systems' contributions are expected shapes system design, but also clarifies the roles and responsibilities in the task performance.

Addressing these questions requires a better understanding of the types of tasks that enable the transport sector to function. Tasks can be differentiated along several schematic categories, according to both the level of cognitive demand to perform the task and the degree of uncertainty under which they are carried out (Cummings, 2014; Rasmussen, 1983). Tasks can be differentiated into:

- Skill-based tasks, which correspond to highly automatic task performance in low uncertainty settings, where information automatically triggers an adapted response with minimal conscious monitoring. Such tasks are often routine and rely on sensorimotor co-ordination that can be developed through training or experience. For example, in driving, when a vehicle drifts too close to a road marking, the driver's learned reaction is to steer back towards the centre of the lane without any deliberate conscious decision making.
- Rules-based tasks involve the execution of established procedures or protocols in response to specific conditions. Unlike skill-based tasks, rule-based tasks happen under higher levels of uncertainty and require the deliberate and conscious application of the sequence. A rule-based task may follow the logic “IF symptoms X, THEN the cause is Y, AND IF the cause is Y, THEN the solution is Z”. For example, train conductors responding to a signalling failure will follow standard operating procedures as set out in safety regulations. These procedures are typically derived empirically from formal or regulatory instructions, ensuring consistency and reliability in task performance. Uncertainty in rule-based tasks can be reduced by establishing clear protocols and ensuring the reliability of information-gathering tools (e.g. sensors).
- Knowledge-based tasks correspond to tasks that primarily rely on situation awareness, reasoning and knowledge to be performed. The completion of such tasks depends on the application of information, expertise and cognitive skills rather than routine efforts or procedures. They imply the highest levels of uncertainty (e.g. unfamiliar situations) and the most advanced levels of reasoning. For example, air traffic controllers managing a disruption in air traffic caused by an incident or weather event must assess evolving weather and traffic conditions, anticipate potential cascading effects and provide real-time responses. This category of task usually implies a high cognitive load.

AI tends to perform well in skill- and rule-based tasks as they are inherently structured and routine. In the case of rule-based tasks, reducing uncertainty and providing clear and unambiguous procedures is essential for maximising AI performance. By contrast, high levels of uncertainty in knowledge-based tasks make full automation more challenging and potentially riskier. Nevertheless, this does not preclude the use of AI in such tasks; rather, it emphasises that AI could be more effective when applied in support of human decision making (i.e. human-AI collaboration) (Cummings, 2014).

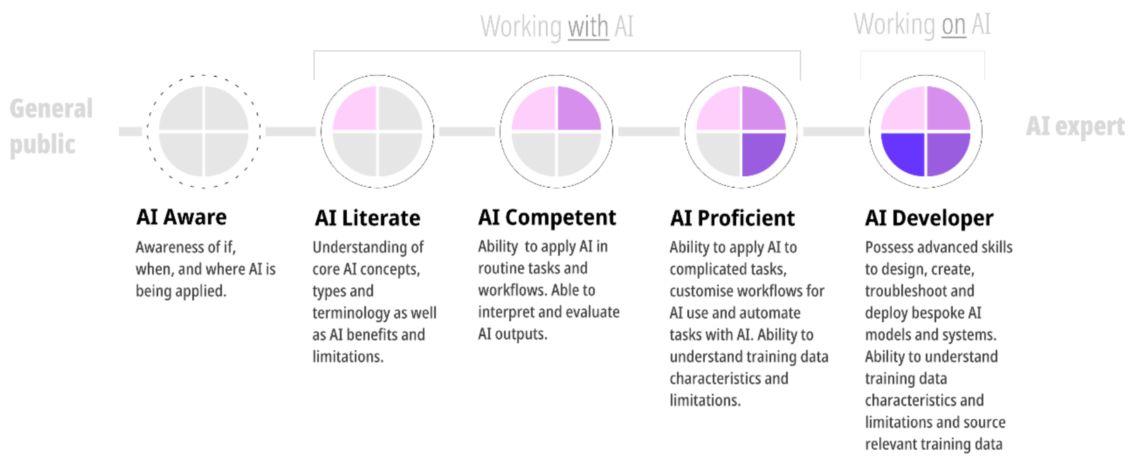
Distinguishing different levels of AI knowledge

The progressive integration of AI in transport activities is changing how transport workers perform their tasks and the nature of work. This reorganisation of tasks often results in changing demand for skills (Green, 2024). While some occupations will require specialised skills and knowledge to work *on* AI models, most workers exposed to AI will not require any skills or knowledge relating to how systems function to work *with* AI. As noted by Green (2024), occupations with high AI exposure will likely demand skills that will complement AI, such as management, business processes (e.g. project management, budgeting, accounting, administration) and social skills. Analysis conducted on a sample of 10 OECD countries shows that resource management, business processes and emotional skills are the three most in-demand skills, with 72%, 67% and 63% of vacancies in the most AI-exposed occupations requiring skills from these categories.

The adoption of AI requires individuals to develop specific knowledge and skills to unlock AI benefits while mitigating its potential risks. The AI knowledge spectrum extends from a basic understanding of what AI is and how it works to advanced expertise. These knowledge levels do not require identical skill sets. As individuals and organisations progress along this spectrum, the type and depth of required knowledge and skills will shift accordingly.

Skills development strategies should be proportionate to the specific requirements of each occupation, ensuring workers gain the skills they truly need for their roles. Several categorisations can be made. A schematic approach would distinguish skills to work *alongside* or *with* AI from those to work *on* AI. Additional layers can be added to reflect the complexity of knowledge required to interact with AI systems. The Alan Turing Institute (2024) distinguished AI citizens (i.e. people who may be users – directly or indirectly – of AI systems), AI workers (i.e. workers whose role is impacted and adjacent to AI), AI professionals (i.e. workers whose main responsibility is related to AI or data) and AI leaders (i.e. individuals with responsibility over the governance of AI systems). From a knowledge perspective, several categories can be identified (Figure 5).

Figure 5. Levels of AI knowledge for workers



Awareness of AI use

A first level of AI knowledge is AI awareness, which describes the capacity of individuals, including decision makers, to be aware of *if*, *when* and *where* AI is being used in transport activities. Awareness of AI use is not about technical proficiency, but rather about the perception and conscious acknowledgement of AI's presence and purpose.

Awareness of AI use is a precondition for deeper knowledge of AI use. It refers to the point at which people are aware *that* AI is being used before they know *how* it is being used. This meta-knowledge is the first step towards broader literacy and proficiency. In this regard, awareness of AI use is less about the understanding of the technology itself, but rather about cultivating a reflective mindset regarding AI use. It prompts individuals to question their assumptions, which is a precondition to forming a more critical understanding of the technology's capabilities and role.

Individuals have different levels of AI awareness. Certain parameters, such as age, wage, level of education or gender, can influence how aware individuals, including workers, are of AI use. In the United States, Kennedy, Tyson and Saks (2023) found that adults with higher levels of income and education tend to demonstrate greater awareness of AI use than other adults. For instance, 53% of individuals with a postgraduate degree correctly identified the presence of AI in specific use cases (e.g. product or playlist recommendation, e-mail service categorisation, etc.) compared to 14% of those with a high-school diploma or less who did so. Authors also found that younger individuals demonstrate a greater AI awareness (35%) in daily life than individuals above 65 years old (18%). Similarly, men tend to show higher awareness of AI use (38%) than women (23%). Beyond the demographic differences, AI awareness also depends on contextual factors and, namely, the type of technology and its application (Ada Lovelace Institute and The Alan Turing Institute, 2023).

Improving individuals' awareness of AI use goes beyond work-related considerations. As AI systems are progressively deployed in the transport sector, informing individuals about where and how AI is used also has a democratic dimension, notably in terms of transparency, accountability and public trust in public authorities' decisions and service provision (Renaissance numérique, 2025). Given that transport systems interact with a large share of the population, transport authorities should ensure that users are informed about where AI is being used, especially in high-risk applications.

AI literacy

The second level of AI knowledge is AI literacy, which refers to general knowledge about AI systems and their functioning. This knowledge includes a basic understanding of the core concepts behind AI technologies, an awareness of the different types of AI systems and their functionalities, comprehension of key terminology used to describe AI systems and a critical understanding of their potential benefits and risks (European Commission, 2024; Renaissance numérique, 2025). The EU AI Act introduces an AI Literacy principle, which provides that:

> Providers and deployers of AI systems shall take measures to ensure, to their best extent, a sufficient level of AI literacy of their staff and other persons dealing with the operation and use of AI systems on their behalf, taking into account their technical knowledge, experience, education and training and the context the AI systems are to be used in, and considering the persons or groups of persons on whom the AI systems are to be used. European Commission (2024), EU AI Act, Chapter 1, Article 4

As AI is progressively being integrated into products and services that shape everyday life, reinforcing AI literacy is essential to equip individuals, including workers, with the necessary skills and knowledge to engage confidently and critically with AI technologies. AI literacy is foundational and should therefore be treated as an educational priority (European Commission, 2025; Renaissance numérique, 2025). The responsibility for developing AI literacy is shared across multiple entities. Educational institutions (e.g. schools, universities) play a crucial role in integrating into curricula the skills and abilities that foster AI literacy. Employers and training providers must support continuous adult learning to enable workers to adapt to the changes brought by AI. Finally, public authorities and policymakers should implement supportive frameworks that promote AI literacy. Efforts to reinforce AI literacy can build on existing frameworks, such as OECD (2025b), Miao, Shiohira and Lao (2024), Miao and Cukurova (2024), and Ministère de l'Education Nationale (2023).

AI Competency

AI competency refers to an individual's ability to apply existing AI tools to help carry out routine tasks and workflows. AI-competent workers can determine which AI technology is adapted to their needs, apply AI technologies in predetermined use cases, interpret the outputs of AI systems and evaluate those outputs with respect to their intended objectives. Part of the required knowledge for AI competency is a basic awareness of the type of data used to train selected AI technologies. At this level of AI knowledge, workers use AI to help them carry out tasks that were defined without AI in mind.

AI Proficiency

AI Proficiency describes the ability for people to not just apply AI to existing workflows, but to design workflows specifically for AI use. Proficient AI users design AI-based workflows to perform relatively complex tasks. As for AI-competent workers, AI-proficient workers must be able to interpret AI-generated outputs, but unlike the former, the latter can redesign tasks and workflows for new types of outputs. AI proficiency relies on both occupation-related expertise and critical thinking to assess the performance and reliability of AI systems.

AI proficiency also involves transition-management capabilities, i.e. the ability to adapt workflows and work activities in case of a failure of the AI system to provide the expected outcome. For example, safety drivers responsible for supervising automated vehicles require far more than standard driving skills; they must be equipped to effectively and safely respond to faulty algorithmic decisions and behaviour. Without adequate training, workers may experience risky situations and stress when compensating for defective algorithmic decisions (Chu et al., 2023).

Ensuring that workers who require AI proficiency have access to appropriate training is essential. These workers must typically acquire and retain two distinct skillsets: the core skills associated with their occupation (e.g. maintenance, driving) that allow them to design AI-enhanced workflows, and the skills and abilities needed to oversee and manage AI systems. The latter can often be acquired through targeted internal training programmes supported by specialised AI certification pathways.

AI Developer

Finally, some occupations' core activity will be related to AI system design, creation and implementation. Instead of designing workflows for AI, AI developers design AI systems for transport tasks and workflows. Workers in these roles will require the knowledge, skills and abilities to understand the transport task at hand, select an AI model type best suited for that task, design and code the model or model instance and deploy the AI system. AI developers must also be able to identify issues in AI systems' performance and propose effective solutions. AI developers are responsible for the design, supervision, maintenance or strategic deployment and use of AI systems. In the transport sector, occupations requiring this level of expertise will likely draw on skill sets that are also in demand in other industries, creating strong competition for AI-development workers across the economy.

From a policymaking perspective, AI-development workers play a critical role in designing and implementing policies and regulatory frameworks that accurately reflect the current capabilities and limitations of AI systems. Their specialised expertise enables them to ensure that policies remain aligned with the latest developments in the field of AI.

Mapping the skills needed in the transport sector as a foundation of effective action

Mapping occupational requirements is foundational for gaining a more comprehensive understanding of workforce levels, and identifying domains and occupations where certain types of skills are more important at a more granular level.

Skills assessment and anticipation: Opportunities and related challenges

Skill mismatches in dynamic sectors are not only possible but also inevitable (OECD, 2016). This reality underscores the importance of continuous monitoring and forward-looking mapping of skills within sectors. In the transport sector, several transformations are driving changes in skill demands, such as the deployment of AI and the transition to low-carbon mobility in response to climate change, including the shift towards electrification of land transport. These transitions are already reshaping the demand for skills and the scale at which they are needed.

Box 2. Australia’s Jobs and Skills Councils

In Australia, Jobs and Skills Councils (JSCs) have been established as industry-owned, not-for-profit organisations under Australia’s Vocational Education and Training (VET) reforms. They constitute a network of councils across various sectors of the economy, each representing a specific sector, and operate in a tripartite arrangement involving governments, employers and unions. Their mandate is to ensure that the skills and workforce requirements for their sector are identified, forecasted and addressed. JSCs aim at improving the relevance and responsiveness of the VET system by aligning training requirements with skills demand, while anticipating future changes.

Industry Skills Australia (ISA) has been established as the Transport and Logistics Jobs and Skills Council. It works on behalf of the transport industry to supervise the development of the national workforce plan based on consultation with transport stakeholders. In 2025, it published Workforce Plans for the aviation, maritime, rail, transport and logistics industries (ISA, 2025a, 2025b, 2025c, 2025d). For each of these sub-sectors, ISA analysed the transformative shifts that will likely impact the future transport workforce. It includes artificial intelligence, sustainability, and existing occupational and workforce shortages.

Source: (ISA, 2025d, 2025c, 2025b, 2025a)

Conducting an inventory of skills provides a more structured and comprehensive way to understand the needed skills in a specific sector. This exercise is a prerequisite for effective policy action as it helps public authorities identify where misalignments (see Table 2) exist between the supply of and demand for skills, and the evolving demand generated by technological, organisational or regulatory changes. While skill mapping efforts exist in all OECD countries, their approaches vary significantly depending on the definition of skills, timespan considered, scope (i.e. national, regional, sectoral) and how they assess current skills needs (i.e. quantitative, qualitative) (OECD, 2016).

Data gathered as part of skill-mapping exercises can inform public authorities on how to update, design or revise skills acquisition strategies, both from an educational and a lifelong learning perspective. OECD (2016) surveyed ministries of labour from OECD Member countries and identified several potential use-cases for skills assessment and anticipation exercises, among which are the update of occupational standards; the design, revision and allocation of retraining and on-the-job training programmes; upskilling or reskilling trainers; developing apprenticeship programmes and designing tax incentives for workers or employers.

Table 2. Sub-optimal labour and skills provision scenarios

Type of mismatch	Definition	Example
Labour shortage	A situation that occurs when there are enough people with the necessary skills in the labour market, but for various reasons, an insufficient number of them are employed in a given occupation or location.	There are critical labour shortages of heavy vehicle drivers (i.e. trucks, buses) as the number of trained drivers is insufficient to meet demand across the economy due to multiple factors, including the ageing of the workforce and difficulty in hiring younger staff because of unfavourable working conditions (i.e. long working hours, relatively low wages). Regional airports may struggle to attract air traffic controllers because trained personnel may prefer to work in major cities, creating a local labour shortage.
Labour surplus	A situation that occurs when the number of people with the required skills seeking employment in a given occupation or location exceeds the number of jobs available.	In some metropolitan areas, there may be a large number of taxi drivers but fewer passengers due to the rise of ride-sharing apps, resulting in a labour surplus.
Skills gap	A situation that occurs when the existing workforce possesses a lower level of skills than is required to perform a job adequately or to meet the occupation's requirements.	Transport administrative staff may face a skills gap if they need to work with AI systems with only computer-related knowledge. Staff will need enhanced digital and AI literacy skills to work more effectively with AI.
Skills mismatch	Refers to the discrepancy between the qualifications and skills that individuals possess and those required by the labour market.	An individual specialised in diesel engine maintenance is employed in general logistics administration because there are no available mechanic roles locally.
Skills shortage	A situation that occurs when the demand for a particular type of skill exceeds the available supply of that skill, resulting in an insufficient supply of the skills needed. This is also referred to as a talent shortage.	As the land transport sector transitions rapidly to electric fleets, there might be a shortage of certified electric vehicle maintenance technicians.
Skill surplus	A situation that occurs when the supply of the workforce with a particular set of skills exceeds the demand for such skills in the labour market.	Experienced ticketing and reservations clerks trained on legacy rail booking systems may face a skill surplus as transport operators increasingly adopt automated online booking platforms. The number of positions requiring these traditional skills has declined, leaving more workers with these capabilities than the market currently demands.

Source: European Labour Authority (2025)

Updating risk assessments and reproducing anticipation exercises can help policymakers, employers and education providers align skills supply with demand and reduce mismatches. What is accurate today can become obsolete in a few years. The impact of AI on workers' expertise and skill demand remains uncertain: it may erode the value of existing skills, while simultaneously creating opportunities for new forms of expertise (National Academies of Sciences, 2024).

Approaches to inventorying skills and abilities

Comprehensive datasets on the transport sector's workforce and skills needs are often missing, both in terms of breadth and quality (NSAR, 2024). This is mainly due to the complexity of the transport sector, the fact that several roles are not solely focused on transport-specific tasks and that some occupations in both freight and passenger transport may not be captured by official data sources (i.e. informal activities). This complexity makes it challenging to draw conclusions about the current skills landscape of the transport workforce.

Existing databases can serve as a starting basis for mapping the transport sector's skills landscape. In the United States, the Occupational Information Network (O*NET) provides a comprehensive overview of occupations' characteristics and requirements. In the European Union (EU), the European Skills, Competencies and Occupations framework (ESCO) provides a similar classification of skills and occupations across EU countries (European Commission, n.d). However, unlike O*NET, ESCO does not indicate how important a given skill is to a particular occupation, nor does it specify the level of proficiency required (OECD, 2019b).

The O*NET-SOC taxonomy (i.e. Standard Occupational Classification) organises occupations in different categories. This report will consider the "Transportation and Material Moving Occupations" major group (SOC 53-000). Sub-categories, with illustrative examples, are outlined below:

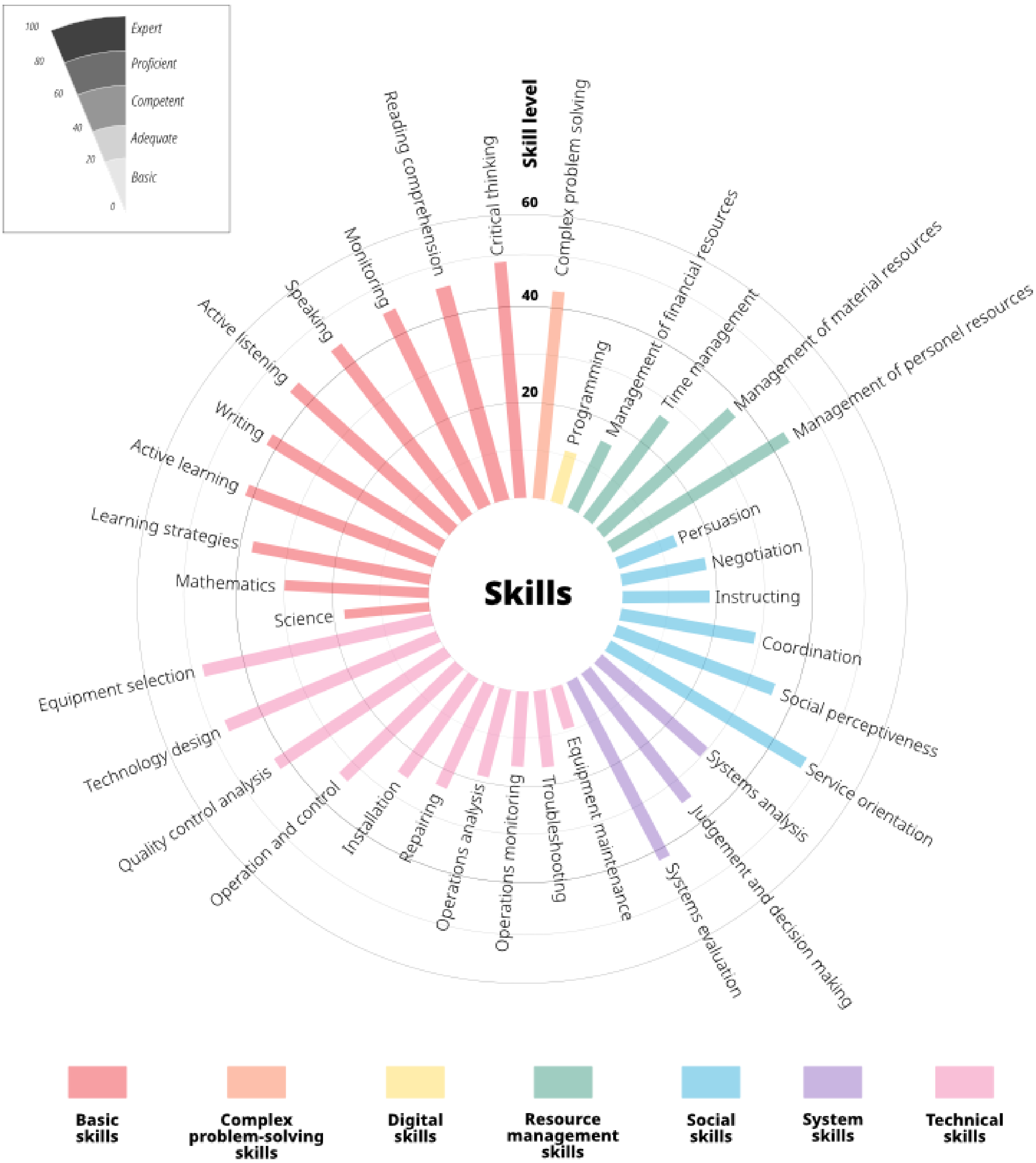
- Major group (SOC 2 digits): 53-000 – Transportation and Material Moving Occupations
- Minor group (SOC 3 digits): e.g. 53-300 – Motor vehicle operators
- Broad occupation (SOC 4-5 digits): e.g. 53-3050 – Passenger vehicle drivers
- Detailed occupation (SOC 6 digits): e.g. 53-3052 – Bus drivers, transit and intercity

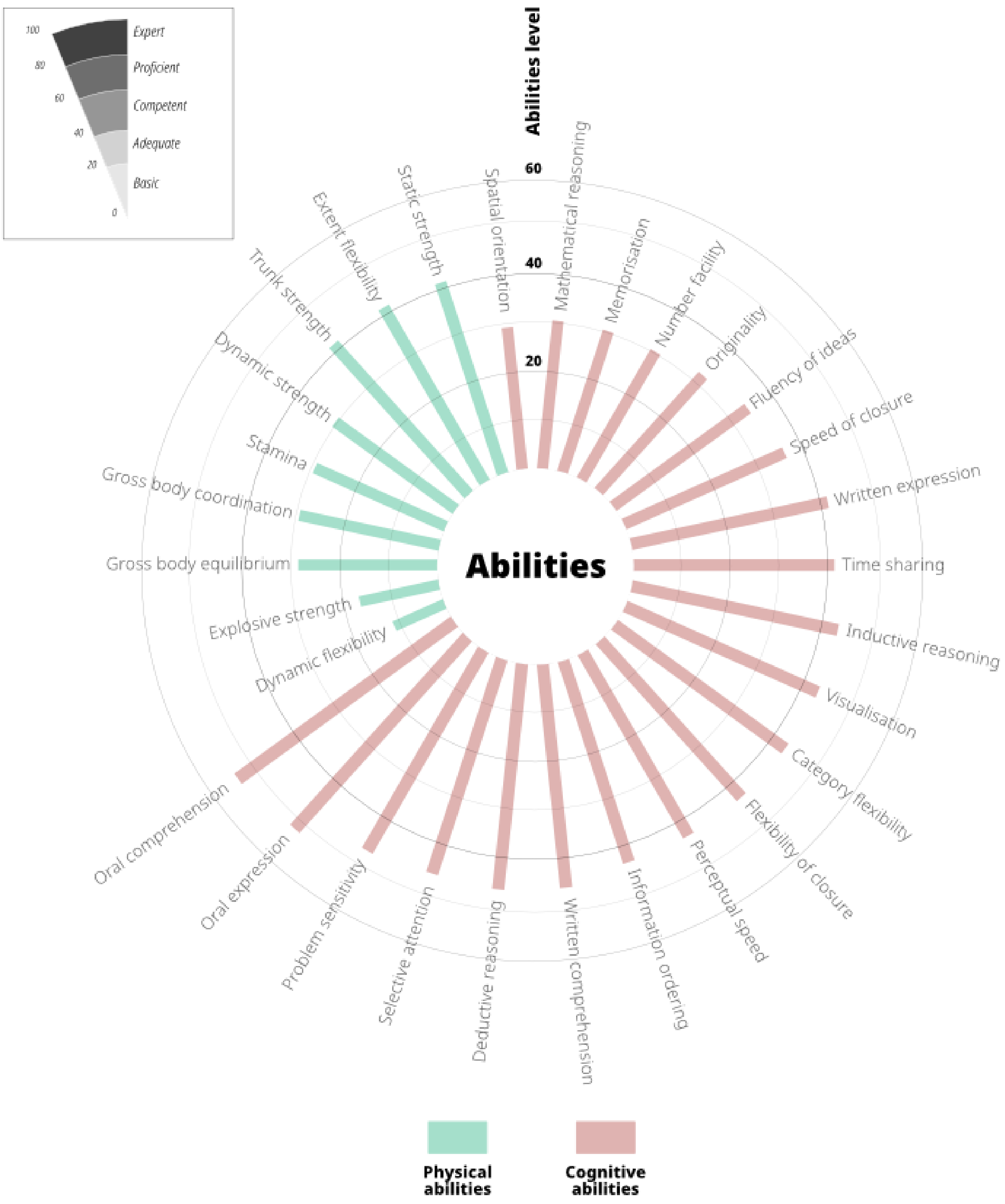
Assessing skills importance and relevance to occupations

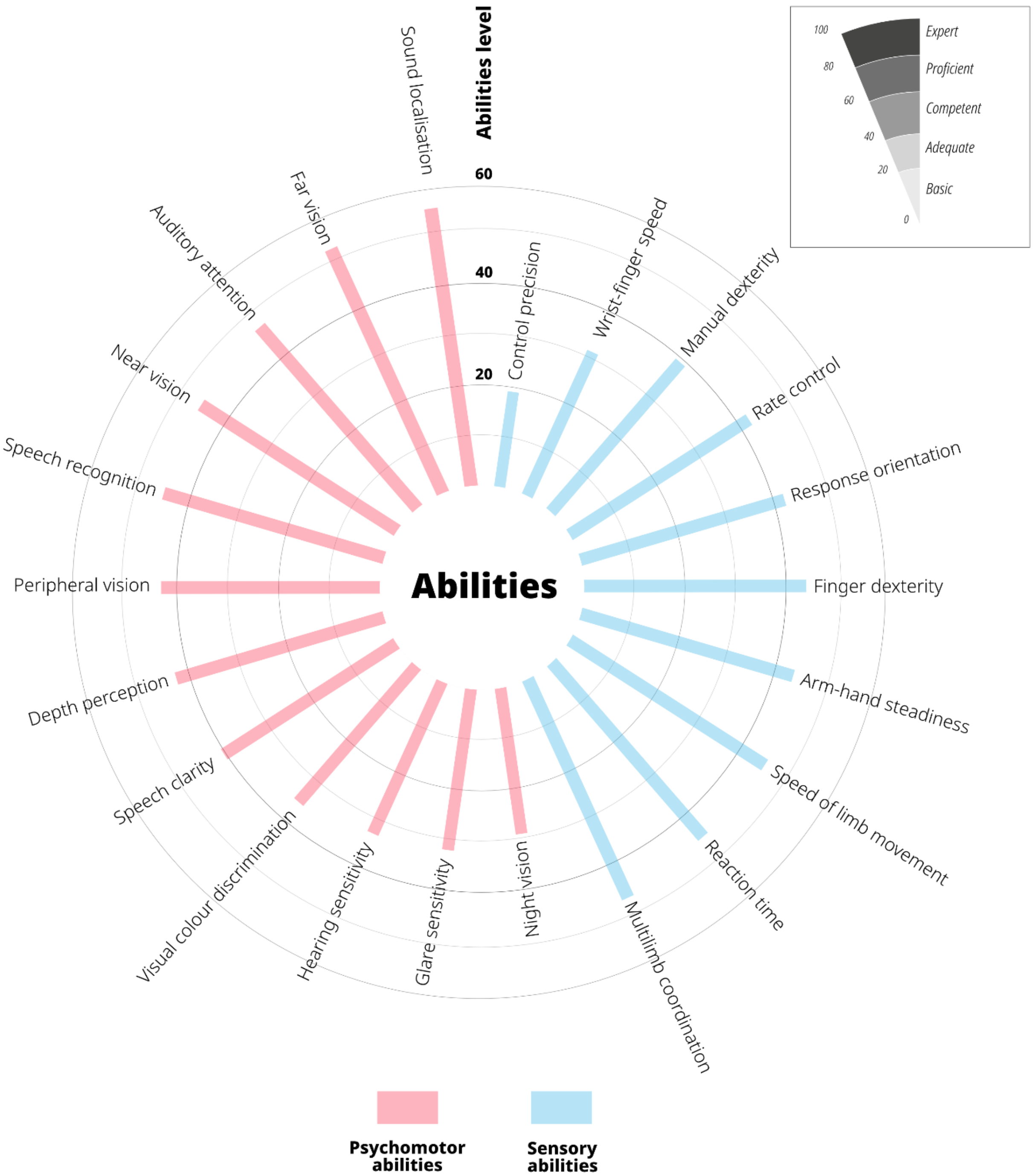
Skills can be rated by their relevance to a given occupation. For example, the O*NET database provides ratings for each skill within an occupation to measure its importance (i.e. "do you need this skill?") and level (i.e. "how good at it do you have to be?"). The following analysis will consider skill level.

The median skills and abilities levels for the occupations in the "Transportation and Material Moving Occupations" (SOC 53-000) are provided below to reflect typical requirements across occupations and to reduce the influence of outliers.

Figure 6. Skills and abilities level in the transport sector




100
80
60
40
20
0
Expert
Proficient
Competent
Adequate
Basic
Abilities level
60
40
20
Abilities
Spatial orientation
Mathematical reasoning
Memorisation
Number facility
Originality
Fluency of ideas
Speed of closure
Written expression
Time sharing
Inductive reasoning
Visualisation
Category flexibility
Flexibility of closure
Perceptual speed
Information ordering
Written comprehension
Deductive reasoning
Selective attention
Problem sensitivity
Oral expression
Oral comprehension
Dynamic flexibility
Explosive strength
Gross body equilibrium
Gross body coordination
Stamina
Dynamic strength
Trunk strength
Extent flexibility
Static strength
Physical abilities
Cognitive abilities



Note: Graphics display the median skill and abilities level required across the transport sector. Levels are measured on a scale from 0 (i.e. the descriptor is not required) to 100 (i.e. the descriptor is essential).

Skill level indicates the degree or point along a continuum to which a particular descriptor is required or needed to perform the occupation. The data on abilities have been presented in two separate graphs to enhance clarity and readability. A bar chart illustrating these data is provided in "Annex B. Skill and abilities levels in the transport sector".

Source: O*NET

Occupations in the transport sector are characterised by moderate to high requirements in cognitive and basic skills, reflecting the sector's reliance on human judgment with complex, time-sensitive systems. As shown in the first chart, the three highest median scores are oral comprehension (54), oral expression (52), and critical thinking (48), highlighting the importance of reasoning, communication and decision making. These capabilities support the interpretation and communication of information to enable co-ordination among transport systems stakeholders as well as the ability to respond appropriately to events. Foundational skills, such as reading comprehension, oral comprehension and expression, speaking, co-ordination and active listening, also play a vital role across most occupations, clustering around a skill level of 40. This suggests they form the core competence base of the transport workforce rather than being confined to specific occupations.

Physical and psychomotor abilities display moderate levels (around 30). This indicates the remaining relevance of physical effort in a sector where task performance is increasingly facilitated by technology (e.g. robots, AI). As shown in the second chart, the relatively low level of need for skills such as raw strength, speed of limb movement and dynamic flexibility is consistent with the growing role of automation in the transport sector. While this shift reduces physical strain, it increases the importance of cognitive oversight. However, the relative importance of abilities such as manual dexterity, control precision and reaction time indicates the importance of human input, particularly in human-machine collaboration, to address real-world variability.

Sensory abilities score higher ratings, especially those linked to safety and situational awareness. As shown in the third chart, abilities such as night vision, near and far vision, selective attention and hearing sensitivity display comparatively higher ratings. This reflects the requirements for overseeing operational environments in transport work, where transport workers must detect subtle cues in dynamic surroundings and maintain vigilance for extended periods. A high level of competence in these areas is essential to improving transport safety as detection and perception failures can lead to adverse outcomes.

By contrast, digital and technical skills, including programming, technology design and certain forms of systems analysis, show lower levels (often below 30). While these skills might be essential for specific specialist roles (e.g. data scientist, AI engineer) and in narrower occupational segments (e.g. app-based mobility services), digital skills are not yet pervasive across the sector as a whole. This indicates the importance of operational knowledge and capabilities within the transport sector.

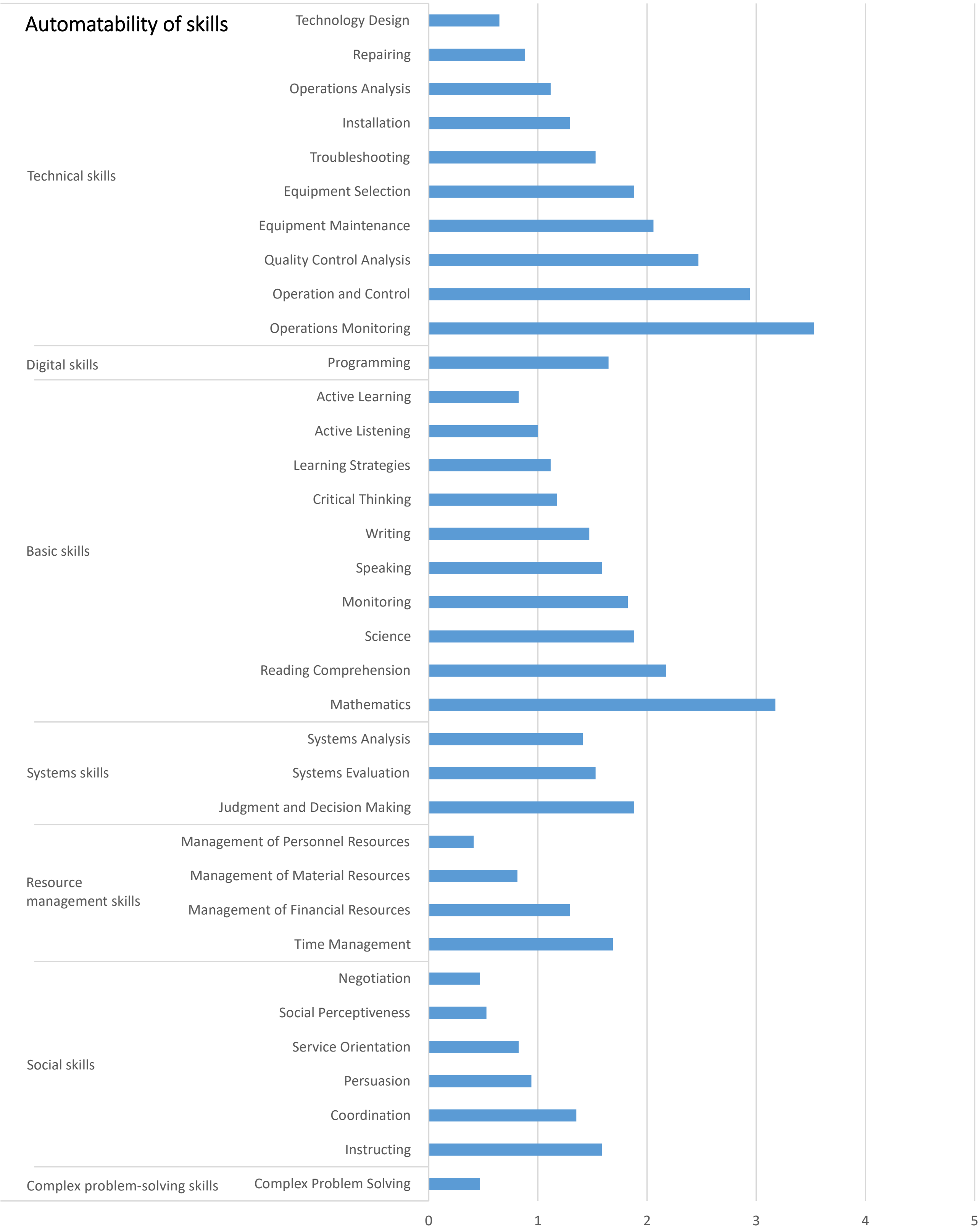
How AI impacts the demand for skills and abilities

Recent advances in AI have significantly expanded the range of skills and abilities that can be replicated by automation technologies (Lassébie and Quintini, 2022). Some skills are more susceptible to potential automation, i.e. they face a higher “risk of automation” or greater exposure to AI. AI exposure refers to how much AI capabilities overlap with human capabilities required to perform a set of tasks as part of an occupation (Pizzinelli et al., 2023). Following skills mapping, public authorities should assess which skills are and are not yet automatable. This will enable them to better target skill acquisition policies towards workers exposed to AI, and to upskill and attract highly demanded skills.

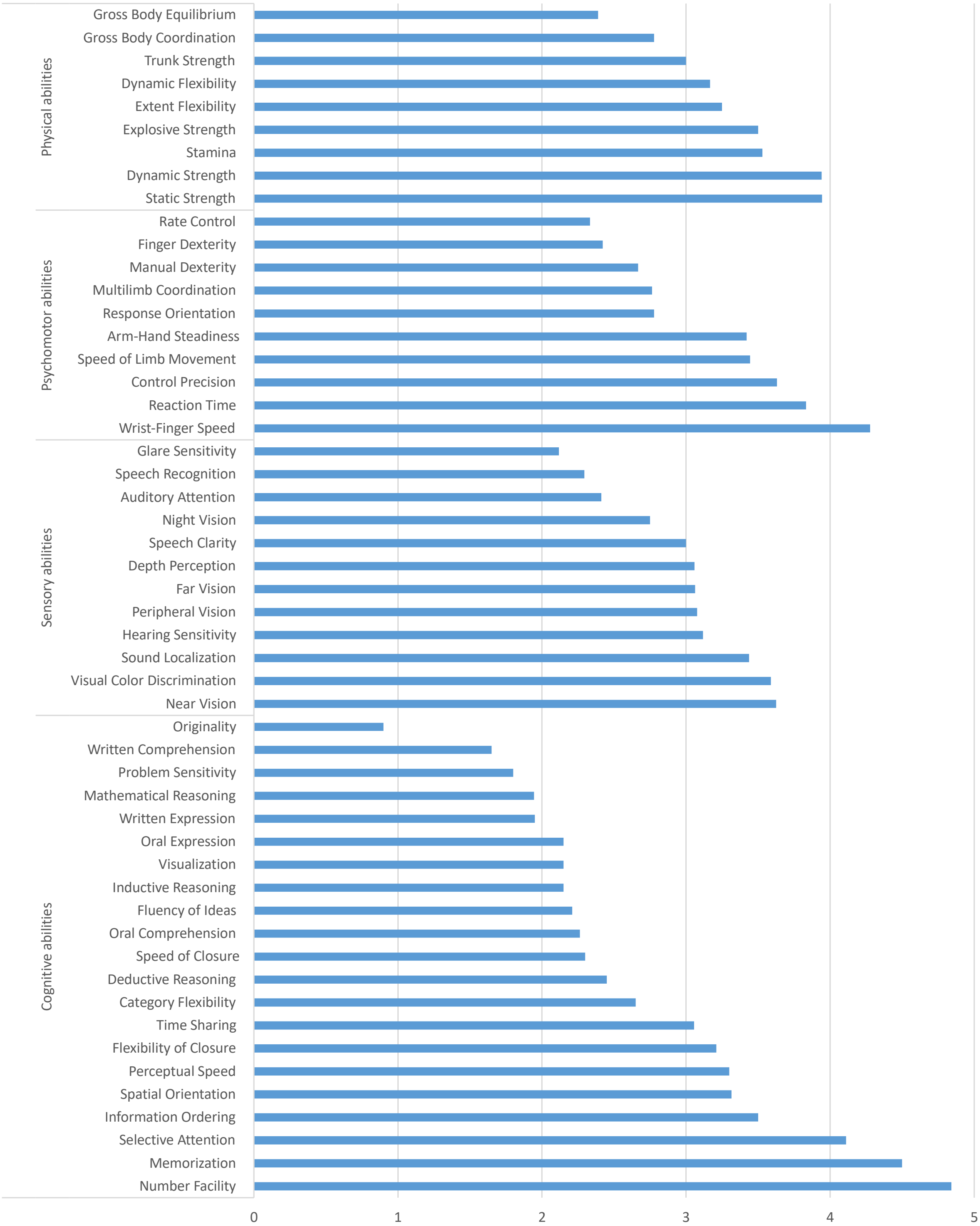
Assessing the automatability of skills and abilities

One approach to assessing the automatability of occupations is to conduct expert surveys to estimate the degree to which a technology can replicate human skills and abilities to perform tasks related to specific occupations. Unlike analyses focusing on technological progress (see Felten, Raj and Seamans (2021), expert surveys can broaden the scope by identifying not only highly automatable skills and abilities, but those that are not yet automatable (i.e. bottleneck skills). Lassébie and Quintini (2022) provide an assessment of the degree of automatability of skills and abilities based on an AI expert survey, as shown in Figure 6. The degree of automatability measures the degree of exposure of an occupation’s tasks to automation. It ranges from 0 (very low automatability) to 5 (very high automatability).

Figure 7. Automatability of skills and abilities



Automatability of abilities



Source: Lassébie and Quintini (2022)Note: Calculations are based on the OECD Expert Survey on Skills and Abilities Automatability and O*NET. The skills are from O*NET. Results and their interpretation are the sole responsibility of the author(s). The opinions expressed and arguments employed herein do not necessarily reflect the official views of the OECD or its Member countries. As the underlying study was published in 2022, the rapid progress of AI systems in recent years may mean that some automatability estimates are conservative. Certain skills and abilities could now be more susceptible to automation than indicated by the original data.

For skills, operations monitoring, and operational and control show some of the highest automatability scores. These skills often rely on pattern recognition and rule-based decision making, areas where AI shows solid capabilities. On the contrary, interpersonal capabilities (i.e. social skills, management skills) show a lower automatability score as they tend to rely more heavily on human interpretation and empathy.

For abilities, physical and psychomotor abilities, which involve precision and speed for repeatable tasks, show a higher automatability score. Tasks requiring these abilities are already well supported by robotics and industrial automation. Cognitive abilities, such as memorisation, the ability to concentrate on a task without being distracted (i.e. selective attention), calculation (i.e. number facility) and information ordering are among the highest automatable abilities. For tasks relying on these abilities, AI tends to perform better than humans in terms of efficiency, defined here as the ability to function without disruption, at lower costs and with longer duration (ITF, 2023). In contrast, cognitive abilities involving originality, reasoning, deduction or conceptual understanding show a lower automatability score. They often require open-ended thinking and the ability to adapt to situations where humans tend to retain an advantage.

The level of automatability of skills is highly dependent on the type of AI applied. Distinguishing between different AI systems is crucial because the extent to which a skill is at risk of automation depends on multiple factors, including the type of skill, the AI system used, its maturity, and the quality of data. AI encompasses various technologies, each with different capabilities and degrees of advancement, allowing them to perform distinct tasks (ITF, 2025a). To ensure safe and efficient automation, it is important to select the most appropriate AI system for the task at hand. Large language models and machine learning have distinct strengths and an optimal range of applications depending on the type of data they rely on and the nature of the tasks to be performed. Frey and Osborne (2024) noted that for certain applications, Generative AI cannot be fully regarded as an automation technology because it still requires a human to prompt and select the outputs. These human-driven stages remain essential as they are where creativity, judgment and interpretive skill play a central role; in this context, the AI system augments human capabilities rather than replacing them.

Skills and abilities exposed to AI

Skills and abilities within the transport sector have different proficiency and automatability profiles. The section below provides a comprehensive mapping of skill proficiency levels required in the transport sector, in comparison to each skill and the automatability level of its abilities. It will analyse different profiles depending on the type of capability considered (i.e. skill, ability, basic skill, physical ability, etc.) and the occupation's sub-sector (i.e. air, waterborne, land). Data are retrieved from O*NET for the skill and abilities level analysis (O*NET, n.d.). The automatability index has been calculated using the methodology developed by Lassébie and Quintini (2022).

The complete mapping is provided in Annex C. Mapping of skills and abilities' level and risk of automation in the transport sector.

Skills exposed to AI

A clear pattern emerges across the transport sector: digital skills (e.g. programming), resource management skills (e.g. management of materials and financial resources) and selected technical skills (including technology design, operations analysis and installation) are generally required at relatively low proficiency levels. These skills also exhibit low automatability scores compared to other skill categories.

Reliance on skills is uneven across sectors and occupations. For example, in the land transport sub-sector, occupations such as *Packers and Packagers, Hand and Industrial Truck and Tractor Operators* require lower levels of basic skills proficiency. In contrast, competencies in mathematics and operations monitoring demand a moderate level of proficiency despite being among the skills most susceptible to automation.

On the contrary, certain transport domains rely more heavily on high-level skills that exhibit low automatability. For example, occupations in the air transport sector broadly require a higher proficiency in core basic skills, including active learning, active listening, learning strategies, critical thinking, writing, speaking, monitoring, scientific reasoning and reading comprehension. These skills score between 0.82 (low risk of automation) and 2.18 (medium risk of automation) on the automatability index. Consequently, maintaining and strengthening the acquisition of these skills is essential for sustaining the workforce in air transport-related occupations.

Public authorities should prioritise training for skills that require a high level of proficiency. Their primary focus should be on ensuring an adequate supply of skilled workers, particularly in occupations that are already facing structural shortages. For this category, AI could provide an alternative to performing certain tasks. However, in occupations where skills are associated with higher automatability levels, public authorities should assess the capacity of AI systems to safely automate specific tasks in comparison to human performance. In safety-critical applications, public authorities should place particular emphasis on maintaining and retaining human skills, even where AI systems demonstrate high performance. In these areas, human expertise provides essential redundancy between human operators and machines, ensuring continuity of operations in the event of an AI system failure. This implies not only facilitating training and practice for human operators, but also establishing clear protocols for human oversight, intervention and handover between automated systems and people (ITF, 2025a).

Abilities exposed to AI

Among abilities, most physical abilities (with the exception of gross body equilibrium, gross body co-ordination and trunk strength) and sensory abilities (with the exception of glare sensitivity, speech recognition, auditory attention, night vision and speech clarity) rank in the top one-third of the most automatable capabilities (including skills and abilities). In contrast, problem sensitivity shows a medium-to-high level in the transport sector, while being at a relatively low risk of automation (1.8).

Skills requirements across the transport sector are uneven across sub-sectors. Sectoral specificities show the importance of certain abilities, for example, originality, which scores among the lowest automatable abilities (0.9) and has a higher requirement level in the air transport sector compared to other sectors. Cognitive abilities, and, particularly, oral expression, visualisation and inductive reasoning, are among medium-automatable abilities, and require the highest proficiency in the air transport sector. Ensuring that AI systems safely substitute for human labour in tasks requiring these abilities is thus crucial.

Overall, abilities tend to exhibit higher automatability scores than skills. This pattern may reflect earlier waves of automation in the transport sector, including robotisation. Nevertheless, several of these highly automatable abilities are still required at high levels of proficiency, such as near vision, auditory attention, reaction time, and oral expression and comprehension. These skills are particularly important in safety-critical operations involving, for example, vehicle movement. While the relatively higher automatability scores of these abilities support greater integration of AI systems into workflows, this reliance may, over time, lower the level of proficiency required for these abilities (i.e. lower ability level)

Policies targeting skills and abilities should be guided by a dual principle. First, public authorities should assess if, when and where AI can be used to alleviate shortages and improve efficiency. They should mainly target non-safety-critical tasks or the application of tested and assessed high-performance AI systems. Secondly, public authorities should prioritise the acquisition of critical human capabilities that support safety and the overall resilience of the transport sector. AI systems should be treated not as a replacement for human skill, but as one component, among others, including human labour and non-AI technologies, in an informed and deliberately designed allocation of labour between humans and machines. Decisions on whether to deploy AI should take into account the operational fitness of AI systems, the level of understanding and capability of public authorities in using them and the extent to which their use aligns with applicable legal, ethical, and societal standards and expectations (ITF, 2025a).

AI in motion: Anticipating AI impacts

The boundary between tasks that can be automated and those that still require human involvement is not static (Ford, 2016). This boundary shifts in response to two main parameters. First, the continuous development of AI systems improves their performance in specific tasks. Recent developments in the field of Generative AI, in particular, have significantly enhanced AI systems' capabilities in producing language, image, video and audio outputs on the basis of existing data. Second, the boundary is influenced by the availability of such tools, including their cost and the ease with which they can be integrated into existing workflows. As AI systems become more affordable and easier to deploy, a wider range of tasks becomes economically and practically automatable, further reshaping the division between human and machine labour.

The trajectory of future AI developments and their related impacts on skills are uncertain. Experts and academia are divided on if, how, where and when AI may impact workers' skills. This uncertainty is a major source of concern for decision makers (Lyons and Davidson, 2016): how can public authorities prepare and plan for an uncertain future? Facing this deep uncertainty, public authorities should adopt a more flexible and open approach to formulating policies that frame the use of AI in the transport sector. Such a vision-led approach aims to define a desired future and then work backwards to establish the principles and policies required to align with the long-term set goals (ITF, 2025c).

A proactive approach to steer AI developments should rely on anticipatory governance (OECD, 2025c). This approach is made up of five key elements:

- Guiding principles and shared values: Public authorities should identify guiding principles and shared values to root responsible innovation in future AI developments. The OECD AI Principles provide a set of value-based principles and recommendations for policymakers for trustworthy AI development. The Hiroshima International Guiding Principles for Organisations developing advanced AI systems also provide a set of guiding principles, built on the OECD's (G7G20, 2023; OECD, n.d.).
- Strategic intelligence approaches to AI governance: Public authorities should collect and process information to monitor and support long-term AI governance. From a skills perspective, public authorities can rely on existing initiatives to monitor and assess AI advancements against human abilities, such as the OECD (2025a) Capability Indicators.
- Stakeholder engagement: Engagement with stakeholders that can influence the course of AI development and the adaptation of the workforce (e.g. unions, employers, workers) allows public authorities to anticipate transformations and public concerns, and improve trust in government.
- Flexible governance: Anticipatory AI governance will require public authorities to be agile in adapting to rapid evolutions of AI technologies (OECD, 2025c). Public authorities can promote agile governance by adopting more flexible regulatory approaches (e.g. outcome-based approaches allowing flexibility in how goals are met).

- International co-operation: Finally, as AI is a global issue, anticipatory AI governance systems will need to interoperate beyond borders. International co-operation can be at different levels: international (e.g. UN, World Bank, etc.), regional (e.g. European Commission, UNECE, etc.), multilateral (e.g. ITF, OECD, etc.), or sectoral or topical (e.g. UITP, International Transport Workers' Federation, ILO, etc.).

The capacity of governments to anticipate AI impacts on the workforce will also rely on their ability to both understand the technology and navigate the changes it introduces (DfT, 2024). This, in turn, will require public authorities to increase their staff's AI awareness and literacy. The UK Department for Transport's (DfT) (DfT, 2025) *Transport Artificial Intelligence Action Plan* sets a series of key actions to be implemented by the DfT and the wider transport sector. From a skills and capabilities perspective, these actions aim to ensure that the DfT is equipped to use, regulate, steer and assure AI systems effectively. Actions include collaboration with leading AI companies, where highly skilled AI technicians are usually located to deliver AI apprenticeships and host secondments in transport authorities; assess training needs and deliver adapted training programmes, including for senior leaders; develop an AI community of practice within the wider transport sector and engage with the wider transport sector to inform future skills programmes.

The next section of this report will look more specifically at the guiding principles aimed at transport stakeholders to ensure a skilled, adaptable and resilient transport workforce.

Guiding principles for knowledge and skills acquisition in the transport sector in the AI age

The increasing integration of AI into transport workflows calls for a structured approach to skills development and lifelong learning. This policy framework outlines five guiding principles for ensuring a skilled, adaptable and resilient workforce.

Principle 1: A proportionate approach to skills development

Lifelong learning should be tailored to the individual's aspirations and needs. Adaptation of training programmes is multi-dimensional.

First, it should consider the type of tasks that individuals aspire to perform. Not all occupations will require the same skills, nor the same level of proficiency in those skills. Consequently, training programmes should be tailored to specific job requirements, ensuring individuals can acquire the necessary skills at the appropriate depth. For instance, individuals aspiring to train as an AI auditor or to manage transport contracts and tenders would need a combination of AI-related skills and legal knowledge. However, an aspiring AI auditor would require more advanced AI expertise and a solid understanding of compliance to assess whether systems follow established procedures, while someone pursuing a role in transport contract management would need only foundational AI skills but more extensive legal and regulatory knowledge.

Secondly, training providers must ensure that the content underpinning their training programmes is accurate and grounded in the best available evidence. This also requires verifying that trainers themselves have received appropriate training, highlighting the importance of continuing professional education for teachers and trainers (Nafukho et al., 2023). The level and depth of the training material should also align with the type and nature of the occupation, recognising that different types of roles demand different levels of expertise. Different types of occupations can be distinguished, as follows:

- Frontier jobs refer to new occupations created by the emergence of specific technologies, in this case, AI (Autor et al., 2022). The demand for frontier workers is expected to extend across the entire economy rather than being confined to a single sector. Workers in these jobs are likely to require AI-related knowledge and skills, with a high level of proficiency (i.e. from AI-proficient to AI developer). These occupations will require more in-depth and technical AI-related skills as well as competencies drawn from other humanities and social sciences (e.g. ethics, philosophy, law, etc.). Davar, Seyed and Hosseini (2024) recognise the importance of the humanities in understanding the nature of AI and influencing its direction. In the transport sector, frontier jobs include occupations such as AI engineers, analysts and machine learning specialists who are developing algorithms for automated vehicles or to automate transport authorities' operations. Another example is AI auditors, who ensure that AI systems embedded in various parts of transport systems operate as intended. Complementary roles in AI-related fields, such as data scientists and robotics engineers, form foundational pillars of the transport automation value chain. They are, respectively, critical for collecting and analysing data to support AI systems and developing algorithms for cyber-physical systems involving robots.
- Retooled jobs describe occupations where the job title and core responsibilities remain largely the same, but the skills required to perform them are changing due to the integration of AI in the workplace (National Academy of Sciences, 2025). Knowledge needs in these categories will be

heterogeneous, spanning basic AI literacy and competency, and AI proficiency. This category may represent the largest share of workers needing retraining. Skills development for these occupations may rely more extensively on adult learning and on-the-job learning, emphasising the importance of employee training programmes, apprenticeships and other models for upskilling workers. Within the transport sector, this includes jobs such as transport planner, automated vehicle safety driver, safety monitors, fleet managers, etc.

- Legacy occupations refer to jobs that are likely to remain needed in the economy, even as AI spreads. These jobs may be less impacted by AI integration as they are not defined by a change in the tasks and skillsets required to perform the job. These occupations may only require a basic level of AI literacy and, in some exceptional cases, AI competency for a limited number of tasks. These occupations have two important dimensions: on the one hand, they are grounded in specialised skills and manual crafts that machines or AI cannot yet fully replicate; on the other hand, they continue to be valued by society. In the transport sector, legacy occupations include cleaners, maintenance technicians and operators. While AI may assist in these roles, the core skills and expertise of these workers will remain indispensable. Planning-related occupations, such as transport planners or logistics co-ordinators, will also likely continue to rely on human decision making and contextual understanding, even if AI support on tasks related to data analysis, for example, will likely increase.

Secondly, the selection and decision to participate in a training programme should be justified based on an assessment of the training's characteristics, including its length and overall design.

On the one hand, the duration of training programmes should align with the type of skills they aim to develop (Misko and Korbel, 2019). Training developers must be mindful that the effectiveness of a programme is dependent on its length (Cole, 2008). Managerial pressure to shorten training may be counterproductive: while short courses of certification may fit easily into work schedules, they are often insufficient for acquiring complex knowledge or skills. Additionally, ineffective learning also represents an inefficient use of resources for both the learner and the organisation. Public authorities that provide or commission training should pre-test training programmes, using a control group, to ensure the programme's design and length are sufficiently tailored to produce meaningful learning outcomes (Cole, 2008).

On the other hand, training design should support the effective transfer of learning to the individual. Training design refers to the architecture underpinning a training programme (Chow, Finney and Woodford, 2010; Nafukho et al., 2023). The main training design factors are the training content and the training instruction designs. Content design refers to the type and relevance of training content. It includes the identification of learning goals, the relevance of the content and practices (Burke and Hutchins, 2007). Instruction design refers to the practices used during training and the strategies employed to support learning, such as timely feedback, real-world examples and error-based demonstrations. Training design should reflect the level of risk associated with a given occupation's tasks. For example, an individual training to become an AI engineer working on automated vehicles should be exposed to high-risk scenarios and have opportunities to practise road-safety decision making.

Principle 2: Focus on bolstering enabling and complementary worker skills

The acquisition of new skills is expected to play a crucial role in the successful adoption of AI technologies by the workforce (Brey and van der Marel, 2024). However, there is no clear agreement on which skills should be prioritised to secure a leading position in AI-exposed industries (Rigley et al., 2024). While some skill strategies prioritise advanced or expert-level AI skills, others focus on broader science, technology, engineering and mathematics (STEM) education and training.

Knowledge, skills and abilities are not isolated assets. Reskilling strategies treating skills in isolation (i.e. skills-based approaches) may overlook how skills are actually acquired and how they interact. A more holistic approach views knowledge, skills and abilities as interconnected assets, with dependencies between them, each forming part of a whole (Hosseinioun et al., 2025). In that view, the acquisition of specific skills should be understood in light of other enabling skills that support it. As AI is being progressively integrated in transport operations, workers in charge of deploying or supervising AI will require contextual knowledge and transport-relevant skills to ensure that the use of AI is legitimate and appropriate. For example, an AI engineer developing algorithmic systems for autonomous vehicles will not only require technical expertise in machine learning, but also an understanding of vehicle dynamics and human safety aspects.

In the context of AI, the acquisition of STEM knowledge and skills can facilitate the development and acquisition of AI-related skills (Rigley et al., 2024). This approach recognises the role and importance of enabling skills, defined here as foundational capabilities that support the development and acquisition of more specialised skills. According to this network perspective, enabling skills serve as the nodes that connect and facilitate the acquisition of other skills. For example, Singapore has identified 16 critical core skills (CCS) that it considers essential in any workplace and applicable across job roles and sectors. The CCS are grouped into three clusters: interacting with others, staying relevant and critical thinking. This framework creates a shared basis for employers, workers and trainers, enabling clearer skill recognition and supporting the design of training programmes (Fang, Zhen and Freebody, 2022). Enabling skills play a critical role as they underpin the successful and safe application of AI in complex transport operations. For instance, AI engineers developing algorithms to automate transport authorities' operations will rely on problem-solving skills, critical thinking and reasoning to assess whether AI systems align with and support planned policy and operational objectives. AI auditors will likely require data science and mathematics skills to be able to identify potential discrepancies coming from the data provided by AI systems.

Furthermore, within this interconnected network, the value of acquiring a new skill is dependent upon the individual’s existing skillset and the newly acquired skill’s complementarity with other ones (Stephany and Teutloff, 2024), including transport-related ones. For transport workers, the development of AI-related skills is likely to yield greater value when supported by enabling skills associated with digital literacy, such as mathematics, problem solving and analytical reasoning. The value of a skill is enhanced when it is combined with the skills of other types. Skills such as deductive reasoning, inductive reasoning and the ability to update and use relevant knowledge have high complementarity with digital skills (Buyukyazici, 2024). Among AI-related skills, programming languages and data analytics have strong complementarities as they show benefits in various combinations.

Understanding how knowledge, skills and abilities interact can enable public authorities to design more effective skills-acquisition strategies and more accurately target investment subsidies for training programmes. Transport authorities can prioritise funding for training programmes that focus on developing enabling skills or those that strongly complement an individual’s existing skillset. Such targeted interventions promote more efficient public investment in skills development programmes as well as ensure skills development unlocks higher value for workers.

Principle 3: Retain and develop critical skills to ensure transport resilience to AI failure and unexpected operation

Knowledge, skills and abilities are a foundational economic and societal pillar (Rigley et al., 2024; Weston, 2024). Increasing people's knowledge and skills can increase workers' productivity, while helping individuals live fulfilled lives and contributing to a more prosperous and inclusive society. Skills and knowledge acquisition serve multiple purposes.

Knowledge and skills form an essential societal infrastructural

Knowledge, skills and the outcomes they support allow broader societal systems to function. In that sense, skills and knowledge form a type of essential infrastructure (Star, 1999): the tasks accomplished by a worker serve as the infrastructure on which other workers can build to accomplish their tasks (Bowker et al., 2009). For example, highway maintenance workers are essential for anticipating and identifying potential failures or disruptions in road service, ensuring continuity of service and infrastructure, which, in turn, is an essential foundation for other types of work throughout the economy.

Knowledge and skills contribute to transport sector resilience

For all its potential benefits, the deployment of AI in the transport sector will not eliminate faulty or unforeseen performance that may contribute to disruption and the burdens that it imposes. Errors previously attributed to humans in carrying out tasks will be replaced with upstream human errors in AI system coding, biases stemming from incomplete training data or unforeseen behaviour of the AI systems themselves. This raises three important points regarding disruption and resilience:

1. *Fail-safe performance*: Planning for AI system failures and ensuring the workforce has sufficient relevant knowledge and skills to address these, and still allow the system to function, improves overall transport and societal resilience.
2. *Continuity of service*: Workflows that integrate AI – in particular, workflows for high-risk applications – will require workers knowledgeable enough to safely intervene or take over when AI fails or fails to perform as expected. These workers will need contextual information (i.e. what the AI system was doing, where the failure was) and the skills (i.e. how to ensure the continuity of the task, how to resume system performance if possible) to address the failure. They will also benefit from clear protocols for managing these AI failures (The Future Society, 2025). AI incident playbooks are a key framework for equipping workers with the knowledge and skills needed to address AI system breakdowns. These frameworks should also outline co-ordination mechanisms that clarify what needs to be addressed and how.
3. *Proactive monitoring and maintenance:* Monitoring and maintenance of AI systems is essential, especially in safety-critical applications. Workers will need adequate training to ensure AI systems remain functional, trustworthy and aligned with expected outcomes over time. Maintenance should be anticipated accordingly and built up within skills development systems.

Learning and maintaining core and critical skills

Critical skills will be required to prevent or reduce the severity of those outcomes. These skills and capabilities are necessary to ensure the resilience of transport systems and must be prioritised in skills acquisition strategies.

AI systems are prone to errors and resilience should be built at the workflow level. This workflow perspective highlights the role of “line” workers' skills in reinforcing the transport system's resilience. It also emphasises the importance of developing and retaining critical skills, particularly in safety-critical operations or when reliance on AI introduces unacceptable vulnerabilities. Organisations using AI should recognise that AI systems may be prone to errors and adjust workflows where AI is involved to account for potential failures. Governance should establish a learning-oriented safety culture by ensuring critical knowledge and skills are developed (e.g. learning), maintained (e.g. training) and retained.

Different categories of critical knowledge and skills can be distinguished:

- Understand: The knowledge and skills required to anticipate when AI systems may fail or to recognise when they are failing. This category draws on both practical experience (e.g. on-the-job learning) and a solid understanding of how underlying AI systems operate. For instance, a safety driver of an automated vehicle that relies solely on camera-based perception may anticipate degraded AI system performance in foggy conditions.
- Act: The knowledge and skills needed to act when AI fails (i.e. taking control over AI systems). Critical skills required to act will mainly be task-related and involve both knowledge and cognitive skills, and, in certain cases, physical abilities. Policies should mandate regular training, reinforcing critical knowledge and skills in safety-critical tasks to mitigate skills erosion. For example, within the air transport sector, as noted by Haslbeck and Zhang (2017), the provision of specific training and regular practices is expected to reduce airplane pilots’ skills erosion (e.g. “Use it or lose it”). Such practices should mainly target cognitive skills as AI is often designed to automate cognitive processes rather than other forms of automation (e.g. robotisation). Frequent AI use tends to accelerate cognitive skills erosion (Macnamara et al., 2024).
- Fix: The knowledge and skills to address AI failures and troubleshoot unexpected AI behaviours. This includes advanced, AI-specific expertise needed to conduct system audits, modify code and perform robust pre-deployment testing. These critical capabilities demand a high level of AI proficiency to diagnose issues and AI developer skills to address or fix them. In the context of transport operations, these skills must be complemented by an understanding of operational and safety requirements as well as regulatory frameworks that are applicable. In this context, an AI safety engineer plays a crucial role in ensuring the safety of systems that involve AI in their workflows and implementing mitigation measures in AI models, while ensuring their compliance with existing regulations and guidelines.

Principle 4: Actively address and avoid critical skills erosion, deskilling and mis-skilling

AI will erode some workers' skills as it takes over tasks once carried out by humans. While a certain level of skills erosion is a normal process and worth the countervailing benefits of AI uptake, the erosion of critical human expertise should be considered risky if it lowers workers' attention and mindfulness, and more broadly, overall transport system resilience.

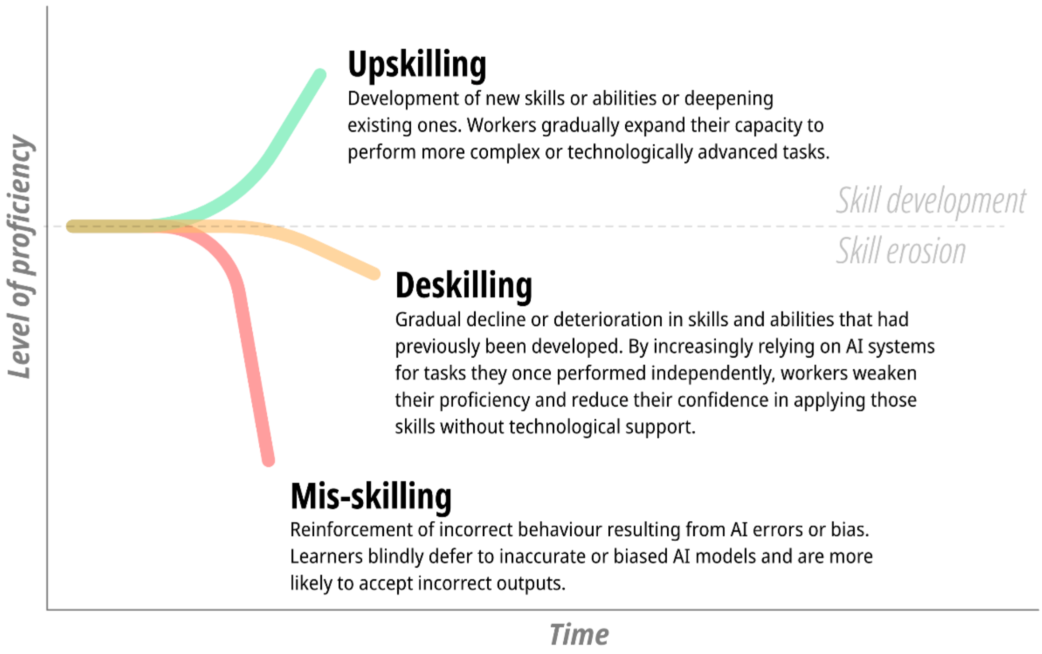
AI and automation, more generally, is expected to reduce the drudgery associated with some workers' tasks. For routine tasks, it may allow workers to cognitively offload tedious tasks and focus on higher-value operations. This benefit relies on both the AI capacity to perform a given task, but also the worker's trust in AI outputs (i.e. automation reliance) (Rinta-Kahila et al., 2023). While AI may yield positive offloading in terms of reducing the burden of work, AI reliance may also raise negative offloading side effects, such as diminished internal cognition and a complacency towards AI outcomes (i.e. automation complacency) (Grinschgl and Neubauer, 2022; Merritt et al., 2019; Parasuraman and Manzey, 2010; Rinta-Kahila et al., 2023).

Automation-induced complacency, or deferral to AI, describes the tendency to complacently defer to AI outputs, leading to a sub-optimal understanding and monitoring of AI performance. Complacency towards automated systems, including AI, can reduce safety: complacent workers may fail to identify, understand, and address automation failures. As highlighted by Funk et al. (1999), airline pilots may become complacent towards autopilot features, leading them to be overconfident in, and uncritical of, automated systems' decisions. This situation can lead workers to delegate their responsibility to the automated system, which can sometimes lead to a worker's failure to act appropriately. In addition, automation complacency can further reduce workers' motivation to actively engage in their tasks. The conjunction of this lack of incentive to develop skills and deferral to AI can erode workers' skills over time (i.e. deskilling). In some cases, it could lead workers to blindly trust AI outputs and adopt their biases and errors (i.e. mis-skilling) (Rinta-Kahila et al., 2023) (Figure 8).

AI complacency can impact transport systems' safety by altering workers' mindfulness of their tasks in different ways (Rinta-Kahila et al., 2023) by:

- Reducing workers' curiosity or understanding of AI system outputs: The apparent reliability of AI systems' outputs may lull workers into a state of incurious and uncritical acceptance of AI system performance.
- Minimising human assessment of AI system outputs: Exposure to AI systems may lead workers to trust AI systems' outputs, and in turn, minimise their own or other people's critical assessment of the system's outputs.
- Lowering incentives to keep up with relevant knowledge: Shifting tasks from humans to AI systems reduces the perceived need for the former to learn and update their task-specific skills and knowledge, even in situations where workers retain legal responsibility for system performance. This facet of complacency also reinforces skills erosion.

Figure 8. Upskilling, deskilling, mis-skilling



Source: Adapted from Abdulnour et al. (2024)

A balance must be found between an acceptable level of reliance on AI outputs and maintaining worker engagement and mindfulness in key tasks.

As workers' skills erode, organisational expertise deteriorates, which can further entrench AI dependency (i.e. AI lock-in) and expose it to new risks. From a skills perspective, organisations may ultimately lose control over their own operations. Measuring AI complacency in organisations is critical to improving the safety of transport operations. At a worker level, understanding which workers may become complacent can further help to target training interventions (Merritt et al., 2019). Skills development strategies should be designed and targeted to mitigate deskilling and prevent the risks associated with mis-skilling.

Public authorities should mandate the maintenance and retention of critical skills within the transport sector. Learning and forgetting skills are inextricably linked (Casner et al., 2014). While public authorities may understand how long it takes to learn a specific skill, they will also need to understand how long it takes to forget it to establish practices and training before critical skills effectively erode. Several authors have noted that, among airline pilots experiencing prolonged cockpit automation, manual control skills are generally retained more effectively than cognitive skills. Cognitive skills require more frequent practice to maintain proficiency (Casner et al., 2014; Mengelkoch, Adams and Gainer, 1971). Additionally, beyond skills retention, regular practice and training can ensure workers retain vigilance over tasks and ensure individuals maintain an acceptable level of confidence in their own unaided judgment (Casner et al., 2014).

Principle 5: Account for the indirect benefits of learning skills and acquiring knowledge

Learning generates benefits that extend beyond the acquisition of specific knowledge, a specific skill itself or their use in a specific context. Many skills are transferable across context and the learning process itself can foster broader cognitive development, curiosity and adaptability. People may also become curious or explore ancillary knowledge or skills as they learn – a "hidden curriculum" of sorts. And finally, the act of learning generates new or adapts existing, cognitive pathways that then constitute new forms of intelligence to be applied more broadly – in this respect, the brain is learning *how to think* as people learn. Deploying AI systems to replicate a skill may improve the delivery of context-specific tasks, but risks losing the other benefits that accrue to workers when they engage in the process of learning and applying skills.

Transversal skills improve individuals' adaptability and resilience

Certain skills and knowledge can be deployed by individuals beyond the specific context in which they were learned. For example, the importance of critical thinking, prioritisation and ranking, and active listening skills extends beyond the workplace. They influence how individuals engage with each other within society. The acquisition of these skills is valuable for societies, even if the related tasks can, to some extent, be automated. Learning allows individuals to adapt to their environment and, in turn, shape it (Lövdén et al., 2020). In this regard, skills acquisition strategies should not be designed solely with work adaptability in mind. Beyond their important value for employability, knowledge, skills and abilities contribute to individuals' personal development and participation in society. Designing skills acquisition strategies with these broader societal outcomes in mind helps ensure that learning systems at different stages of life not only support economic adjustment but the development of resilient citizens, thereby reinforcing the foundations on which individuals' adaptability to the labour market is built. Automation may decrease the exposure of workers to transversal skills and knowledge, and thus erode the overall social value of having an educated and skilled workforce.

Learning ancillary skills – the "hidden curricula" – has value for society

Through education and lifelong learning, individuals assimilate a "hidden curriculum", defined as the knowledge, skills, abilities, values or beliefs that individuals may unintentionally acquire in the process of learning another skill. Learning environments, such as schools, support the development of social and emotional-related skills (Maynard, Warhurst and Fairchild, 2023; Serhatlioglu and Gurol, 2024). For example, the COVID-19 pandemic and its related disruptions, including in-person learning, impacted pupils' acquisition of social and emotional skills, and revealed cognitive gaps (Yates, Young and Mantler, 2025). Maintaining the development of skills and abilities that could be replaced by AI bears a critical role in allowing individuals to develop ancillary knowledge, skills and abilities that may be complementary to AI-related skills.

Learning is not only about what is learned, but how learning teaches the brain to think

At a fundamental level, the human brain learns to think through the act of learning. Neural development exploits the brain's "synaptic plasticity" to encode experience and knowledge into replicable and retrievable forms of cognition that characterise "intelligence" (van Duijvenvoorde et al., 2022; Gazerani, 2025; National Research Council, 2000; Park et al., 2025). The act of learning imprints the brain in ways that differ according to the type of knowledge gained. Reading a book, hearing a lecture, learning a repetitive movement, sorting items on a shelf, singing, learning a language, dancing, etc., all create different synaptic pathways as a person learns these new skills. Crucially, however, those new synaptic pathways can be activated in any other situation faced by the brain. In other words, the acquisition of specific synaptic pathways is unique to what is being learned, but their activation is universal across all kinds of new contexts (van Duijvenvoorde et al., 2022; Gazerani, 2025; National Research Council, 2000). The risk with AI replicating human skills, even some of the most easily replicable and menial ones, is that the human brain no longer gains the cognitive benefits of learning those skills. At the same time, the growing demand for AI-related and enabling skills offers alternative pathways for cognitive development, provided individuals remain actively engaged in learning rather than passive system use.

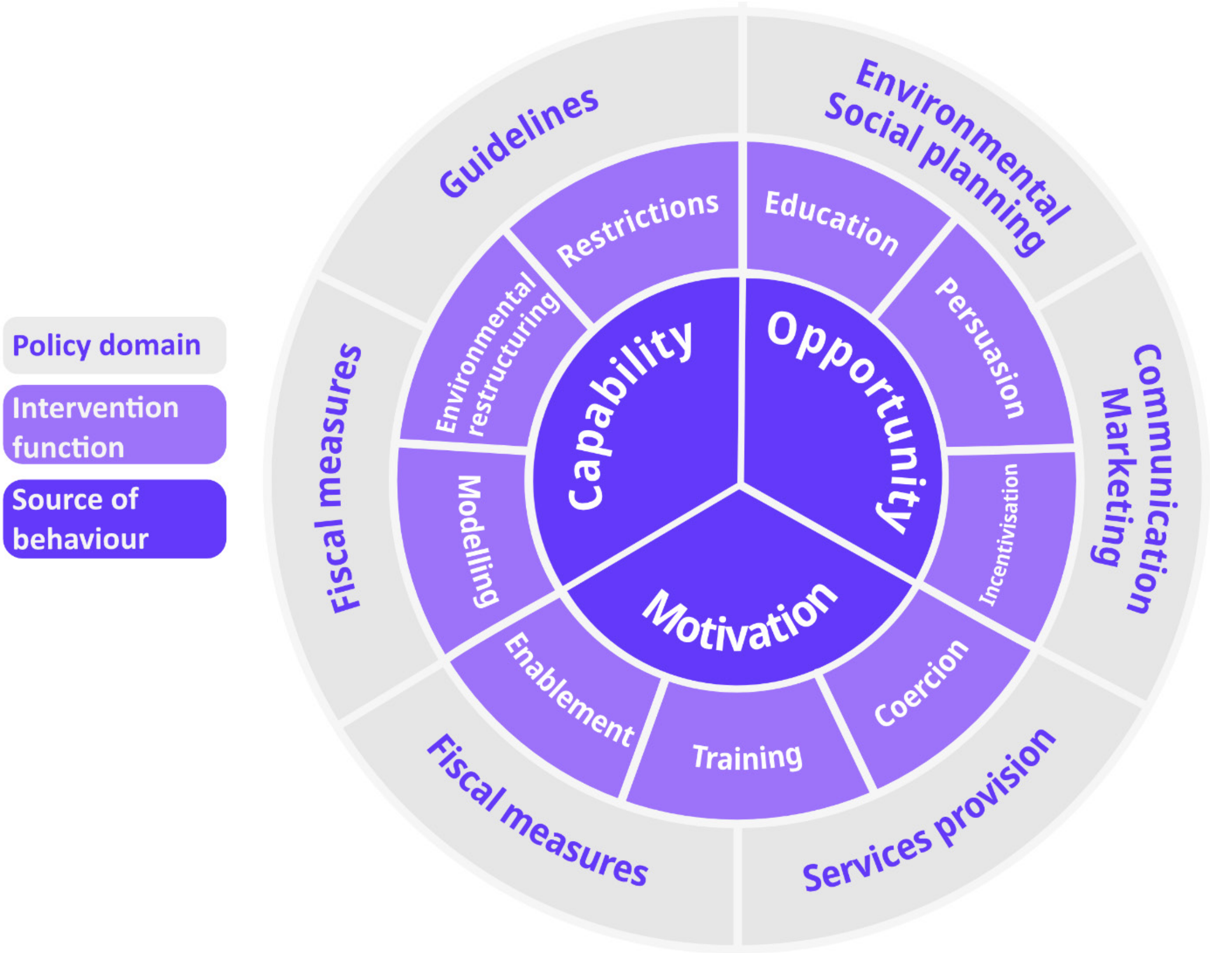
Public authorities deciding on education policies and involved in designing or providing training programmes should weigh the cost of acquiring skills against the cost of not acquiring them. Preventing individuals from learning specific skills and engaging with certain tasks may lead them to accumulate a form of cognitive debt (Kosmyna et al., 2025). As defined by the authors, cognitive debt refers to the short-term deferral of mental effort to perform a task that ultimately results in long-term costs on individuals, including reduced creativity and a lowered capacity for critical evaluation.

Strategies for AI-era transport workforce knowledge and skills acquisition

While previous sections explore various high-level technological, economic and social trends, the following section focuses on the individual. More specifically, it examines barriers workers may face when trying to acquire new skills in an AI era. Each sub-section begins by outlining the challenges workers face and continues with practical recommendations for public authorities to assist workers in overcoming said challenges.

As this section aims to capture the perspective of the individual worker, it utilises the Behaviour Change Wheel, a framework commonly used to integrate psychological and behavioural insights into policymaking across domains to achieve more effective policy interventions (Michie et al., 2011). This is enabled by, first, understanding the underlying barriers impeding a certain behaviour, followed by choosing the most adequate intervention functions to address these barriers and, finally, identifying the policy category that could enable those interventions to occur (See Figure 9). One of the reasons this framework is acclaimed by many academics and practitioners is that it focuses on understanding the underlying issues from the perspective of the individual, while matching solutions to a comprehensive toolbox from the perspective of policymakers.

Figure 9. The Behaviour Change Wheel



Source: Authors, based on Michie et al., 2011

To apply the Behaviour Change Wheel, each sub-section begins by examining one of the underlying psychological barriers (and enablers) placed at the centre of the wheel: capability, opportunity and motivation. It continues by identifying interventions to address these barriers (the middle circle), while specifying the recommended policy domain (the outer circle). This ties the perspective of the individual worker (i.e. the source of behaviour) to the perspective of the public servant in transport authorities (i.e. intervention function), up to the perspective of higher-level public servants and elected officials (policy domain).

While the listed barriers and proposed interventions are not exhaustive, they are meant to inspire policymakers to take a similar approach in their specific context by adopting this human-centred approach. To design calibrated policy interventions, in-depth analyses of the specific condition are required.

The motivation barrier: Limited understanding and uncertainty about the relevance of new skills

Motivation refers to the internal processes that energise and direct behaviour. It encompasses both reflective motivation, such as conscious evaluations, beliefs and intentions that shape decision making, as well as automatic motivation, which includes emotions, impulses and habits that drive or inhibit action (Michie, van Stralen and West, 2011). In the context of workforce development, a worker's underlying motivation shapes whether they view upskilling as necessary, desirable and attainable. It also influences their existing learning habits, and their emotions and attitudes toward acquiring new skills in response to AI. Workers' level of motivation, acceptance of change and engagement are critical factors that significantly influence the success of digital transition (Jenkins, 2021; Kalenda and Kočvarová, 2022).

What workers face

Several large datasets show a motivation gap in terms of workers' willingness to acquire new skills that integrate or adapt these new technologies (e.g. Jenkins, 2021; Kalenda and Kočvarová, 2022). While many factors can explain workers' low motivation to gain new skills, the three underlying psychological constructs discussed below can have a particularly strong impact on motivation and subsequent upskilling behaviours.

Limited understanding of AI presence and its practical implications for daily tasks

As previously discussed, AI knowledge spans over five levels, with the first category being AI awareness. Given that most people do not identify the presence of AI in many use cases (Kennedy, Tyson and Saks 2023), it is very likely many workers do not recognise the extent of the impact AI will have (and to some extent is already having) on tasks related to their jobs. In the transport sector, surveys show that, although white-collar transport workers tend to have relatively high educational backgrounds, their self-reported AI knowledge, defined as familiarity with AI concepts and AI technologies, remain modest (CIHT, 2024). Without a clear understanding and concrete information about how AI influences their lives directly, people may lack the internal motivation required to develop skills that respond to these technological trends. Overall, poor AI awareness, literacy or competency makes workers more vulnerable to displacement as AI systems become embedded in operations (ITF, 2023).

Anxiety about technology-driven workplace changes

While gaining a basic understanding of AI functionalities and applications is a critical first step toward upskilling, people who are aware of the increasing impact of AI may face yet another barrier: anxiety. Several early findings indicate that awareness of AI can be linked to lower emotional well-being at work because it triggers stress about job replacement or reduced earnings (Jin, Jiang and Liao, 2024; Zheng and Zhang, 2025). Moreover, it seems transport sector workers are more pessimistic than optimistic regarding the impact of AI on their work: in a study by the Pew Research Centre it was found that 21% of U.S. transport workers believe AI will have a negative impact on their work versus 16% who feel it will have a positive impact (Pew Research Center, 2025).

This negative perception of AI may influence how workers in the sector interpret the value of training and upskilling: when AI is seen as a displacement risk rather than an opportunity to upgrade one's role, it can provoke defensive reactions that weaken motivation to learn and adapt, and trigger avoidance behaviours instead. This notion is further supported by recent work showing that perceiving AI as a threat can trigger fear-driven avoidance, which translates into hesitancy to use generative AI tools (OECD, 2025d).

Uncertainty about future skill requirements

Another critical (and often underestimated) barrier to workers' motivation to upskilling is uncertainty around specific skills in the transport sector that will be valuable in an AI era. The lack of consensus around what skills should be prioritised in AI skills policies indicates that the level of ambiguity is very high, even among experts and relevant decision makers (Rigley et al., 2024).

Such an uncertain environment makes it difficult for individual workers to decide how to best invest their time and energy. In times of fast-moving technological changes, workers may adopt a rational "wait and see approach" (Khan, Nasim and Rasheed, 2024). Workers may doubt that training will improve their employability or fear that newly acquired skills will become irrelevant before their investments transform into career progression. This, in turn, increases hesitation and reduces willingness and motivation to act in the first place.

How policymakers can address these challenges

Overcoming the motivation barriers identified above requires a tailored set of interventions that address the psychological impacts of technological transitions. The strategies discussed below provide policymakers with intervention functions that tackle each of the motivational pain points identified above.

Education: Increasing knowledge and understanding of AI without anxiety-raising

As discussed in the previous sub-section, while raising AI awareness and understanding is important, when done incorrectly, it may actually raise anxiety among workers. To avoid triggering counterproductive anxiety, policymakers should show how AI can support transport workers' tasks, while openly discussing how these changes will affect workflows in the foreseeable future. The goal is to emphasise that AI can be an opportunity for professional development rather than an immediate and imminent threat to employment. Azerbaijan's AI strategy for 2025-2028, which provides a series of actions to improve talents and skills in the field of AI, aims to increase the knowledge and understanding of AI by raising public awareness of AI use, especially regarding responsible and ethical AI applications. This objective is supported by the establishment of an AI Academy, a training centre created by the National AI Centre, which provides training and learning programs from basic AI concepts to more in-depth STEM-based knowledge (Republic of Azerbaijan, 2025).

Recent initiatives suggest this approach is feasible. For example, SNCF, a French state-owned rail company, has introduced a company-wide AI training programme, including a "Prompt Academy", that has trained 20 000 employees. This training has exposed employees to various useful ways in which AI can support everyday responsibilities, such as customer information, maintenance planning and energy-efficient operations. This approach helped frame AI as a tool for workers to use in a concrete manner rather than abstract agents that threaten to render their jobs obsolete (SNCF Groupe, 2025).

Modelling: Build trust and psychological safety through partnerships

Public authorities should partner with industry associations and worker unions to boost upskilling, both through improved communication and co-design of upskilling pathways. This approach can reduce anxiety as it sends a clear message to workers that trusted actors are collaboratively shaping this transition. When people see that AI solutions are endorsed by organisations that look out for their interests, perceived threat declines and motivation to learn increases.

In addition, stronger collaboration between transport authorities and AI specialists is key to creating a better understanding of how AI solutions can address operational needs and designing AI training accordingly (CIHT, 2024). For instance, SNCF's internal "SNCF Group GP" development process included business/ICT specialists and was rolled out to operational staff and support functions (SNCF Groupe, 2025). Partnerships should be formalised through structured initiatives, such as a sector-wide skills pact. For example, the EU Pact for Skills and the Automotive Skills Alliance provides a good model since it can bring together operators, manufacturers and training providers under a shared commitment to annual upskilling targets (e.g. 5% of the workforce per year). Moreover, public authorities should consider collaborating with external service providers who may be able to offer a variety of AI training for transport professionals.

Such combined public commitments, coupled with worker participation, increase credibility and reduce perceived threat which, in turn, support worker motivation and reduce psychological stress.

Enablement: Reduce uncertainty through clear and consistent skills signals

While many of the inherently unknown factors around AI's influence on the transport sector cannot be resolved by policymakers, they can nonetheless reduce some of the uncertainty workers face by focusing attention on skills that are likely to be useful in the short and medium term. More specifically, policymakers can still provide guidance by endorsing a set of priority skills and competencies that are likely to remain relevant across evolving scenarios, as identified in this report (see Annex B).

This involves identifying and clearly communicating the specific skills and knowledge categories required, depending on context. For instance, The Land Transport Authority of Singapore published a public, role-based, transport-specific skills taxonomy that helps workers identify skills that matter and when to acquire them (SkillsFuture Singapore, 2018). Another example of a transport authority actively indicating priority skills comes from Transport for London (TfL). TfL developed a Digital Skills Capability Framework for all transport workers in the organisation, which has proved useful in reducing worker uncertainty during digitalisation (TfL, 2024).

Going beyond a reactive "wait and see" approach, policymakers can proactively search for "quick and safe" wins from AI tools that are already deployed (ITF, 2025a). This can be achieved by identifying concrete use cases where AI helps workers perform their job more easily. For example, Deutsche Bahn (DB) is testing and deploying an AI system for visual diagnostics that works together with the maintenance staff. Cameras positioned over tracks capture images as trains pass and automated image analysis flags damage within minutes. Maintenance staff receive targeted alerts instead of inspecting trains manually. This raises capacity and cuts time spent on physical checks, such as climbing onto roofs (Deutsche Bahn, n.d.). These kinds of examples help highlight tangible returns from AI, reducing uncertainty among staff about potential competition between them and the technology.

The capability barrier: Financial, time and resource limitations

Capability in the Behaviour Change Wheel framework refers to both an individual's psychological and physical capacity to perform a behaviour. Psychological capability encompasses the knowledge, skills and abilities required for action; physical capability includes the time, stamina and access to resources needed to carry it out (Michie, van Stralen and West, 2011). In the context of AI upskilling, psychological capability includes elements such as workers' digital literacy, learning confidence, and the time and energy required to acquire and practice new skills. Physical capability includes having the strength, stamina or dexterity needed to gain a new skill. In the context of AI skills acquisition, this refers to the presence of enabling conditions that permit workers to develop necessary skills, including financial resources, available time and access to training infrastructure.

What workers face

Time poverty and inflexible schedules

Time poverty, defined as a lack of free or discretionary time, can severely hamper workers' capability to engage in any kind of upskilling, both by reducing the hours they can devote to learning as well as by undermining cognitive capacities, such as attention and memory.

Across OECD countries, lack of time is the single most frequently cited barrier to upskilling in adults. Women are more likely than men to mention time scarcity as an obstacle to learning (27% vs 20%). This gap holds even after accounting for occupation, education and socio-demographic factors (OECD, 2025e). Eurostat (2024b) also supports this notion, indicating that time constraint is the leading cause for unmet or limited training uptake. In the transport sector, this problem is especially acute as shift work and night operations leave little flexibility to attend formal courses. Transport workers who finish long or irregular shifts tend to experience both physical and mental fatigue, which reduces the cognitive capacity needed for learning and acquiring new skills. Moreover, when people are rushed or tired, they are more likely to avoid training, forget material more quickly or engage in shallow rather than deep learning (Leso et al., 2021).

Cost and income risk

OECD and European Centre for the Development of Vocational training (CEDEFOP) surveys consistently rank high costs among the top three reasons for non-participation in training programmes (CEDEFOP, 2025; OECD, 2023, 2025e). Training costs consist of both direct and indirect (i.e. opportunity) costs, which limit workers' physical and psychological capability to participate in training programmes. Examples of direct expenses include course fees, transport and childcare, among others. Opportunity costs can be even more significant: transport workers, especially people working shifts, may have to forgo income to attend training. Paradoxically, lower-wage and part-time workers are least able to absorb this income loss, yet they are also the least likely to receive employer-supported training opportunities (OECD, 2025e). This creates a capability trap: workers cannot afford to pay for training on their own and employers often do not provide it.

How policymakers can address these challenges

An effective policy response that increases learning capacity spans the entire learning lifecycle, starting at early education, through higher education and workplace learning. Yet the transport sector cannot address every gap in this learning process, which is why transport authorities should focus on areas where they have direct influence and collaborate with education and labour-market institutions to support the evolving needs of the transport sector.

Incentivisation: Establish paid training leave schemes and a flexible learning infrastructure

To reduce the impact of time poverty in the transport workforce, public authorities can incentivise employees with paid training leave and wage replacement. Evidence from OECD work on individual adult learning highlights that paid training leaves with adequate wage replacement can increase participation in training and improves skills (OECD, 2025f). This can benefit a large portion of transport sector workers, particularly blue-collar workers. One successful example comes from France, where an individual learning account called *Compte personnel de formation* (CPF) can be combined with the *Projet de transition professionnelle*, a training scheme that allows employees (including bus, rail and logistics staff) to take extended time off for certifying courses while maintaining part or all of their salary (Perez and Vourc'h, 2020).

Another approach is for transport authorities to encourage operators to designate learning time within paid work hours, for example, by allocating the last hour of a shift to skills development and rotating workers through training slots. As many employers in the transport sector face labour shortage, this approach may be more viable than finding a replacement for workers who are on training leave for extended periods of time.

One interesting example comes from Germany, where an initiative by Barnimer Busgesellschaft (BBG), a regional bus operator, applied such an approach. BBG identified that long, usually unpaid breaks between drivers' split shifts could be converted to paid time when used for learning: during these breaks, drivers can log into short e-learning modules on their phones, with learning time and completion tracked in the company's system. The improved knowledge of routes and technical procedures that drivers gain in these sessions benefits both the drivers and the company. BBG reports that drivers value this arrangement and that it even supports the company's positioning as an attractive employer.

Transport authorities can assist in the development of such training schemes that accommodate the operational realities of transport workers. As the BBG demonstrates, this includes developing modular learning formats that workers can access at times that fit irregular schedules. Public authorities could help fund the creation of these learning modules, specifically designed for technicians, drivers and other frontline staff. This can help workers handle time constraints better as they would build competencies incrementally without requiring multi-day absences from work. Moreover, offering micro-learning modules can help workers overcome lack of confidence as these role-specific, modular offers do not necessarily require extensive digital or academic backgrounds.

Enablement: Ease the financial load on both workers and employers

Public authorities can provide training subsidies that cover course fees to some extent. This can be applied by replacing lost income when training reduces working hours, providing childcare support or helping cover part of the costs of equipment needed for online learning. This is particularly important for contingent workers or workers in small companies, where employers often do not support training financially. Luxembourg's individual training leave scheme illustrates how public authorities can reduce training costs effectively. Employees who take approved training leave can receive a compensatory allowance (based on their average wage). Though paid by the employer, the state reimburses the company, including the employer's social security contributions.

That said, public support for skills development does not necessarily mean that training should be free or financed entirely by the public authority as effective adult learning systems rely on shared responsibility (ITF, 2023). Public authorities can explore co-funding schemes that include employers and individuals, distributing the financial burden of training across many actors.

Many OECD countries already fund training for workers and job-seekers (OECD, 2025g). These training schemes can be built upon to extend courses to include AI-related skills, better preparing workers in the transport sector for the AI era.

The opportunity barrier: Limited access to high-quality training opportunities

While capability focuses on whether workers could learn if they had the necessary *personal* resources, opportunity concerns whether the *external environment* supports or impedes learning. Thus, opportunity refers to the external conditions that enable or constrain a certain behaviour. Physical opportunity relates to what tangible elements an environment allows, such as resources, location and logistical constraints. Social opportunity, on the other hand, focuses on the attitudes and behaviours of other people, such as peers and supervisors as well as broader organisational norms that legitimise (or discourage) learning activities (Michie, van Stralen and West, 2011). Even when workers are motivated and possess the necessary baseline capabilities, learning can be constrained if the physical and social environment does not support skills acquisition.

In the transport sector, various circumstances can come together to create an environment that discourages learning. Such factors include insufficient training infrastructure, geographic distance from training centres, delivery formats that do not accommodate shift work and more. These structural constraints limit the practical feasibility of upskilling, even for workers who are willing and able to upskill.

What workers face

Physical access to training infrastructure

The geographic dimension of opportunity barriers can be especially problematic for the transport workforce, which is (by design) spatially distributed across routes, regional hubs and remote operational sites. For many workers in these locations, geographic distance and physical access to educational opportunity remain challenges to accessing education and training (OECD, 2025h). Even online training is not always a reliable solution, since rural or peripheral areas in some countries may have unstable Internet connectivity (Valencia-Arias et al., 2025).

Social opportunity, organisational culture and systematic bias

Social opportunity concerns the extent to which workplace culture, managerial attitudes, peer norms and organisational processes create an environment that encourages active learning. While social opportunity is a crucial condition for learning, 76% of Learning and Development professionals feel that upskilling is not a management priority and 64% think that management views learning as a cost rather than an investment (CIPD, 2020). When such attitudes are faced with operational pressures, the social environment may even actively discourage workforce development (O’Regan, Stainer and Sims, 2010).

These social dynamics can be exacerbated by systemic biases related to gender, age, race and physical ability, which may further influence managerial decisions about who receives training opportunities and whose development is viewed as worthwhile. Such biases can limit the perceived legitimacy of learning for some groups, further reducing their access to AI and digital skills development.

Quality and relevance of available training

Even when training programmes do exist and can be accessed by workers, they may not match transport workers' professional needs. This issue is reinforced by the previously mentioned lack of consensus surrounding curricula and relevant skills in an AI era. This situation may be taken advantage of by opportunistic providers who exploit the ambiguity surrounding training avenues and the hype around AI to promote courses that are of poor quality or irrelevant to transport workers. The quality of training is directly correlated with the readiness of training infrastructure and providers to provide relevant training. Azerbaijan's AI strategy 2025-2028 identifies the importance of preparing and attracting AI trainers to achieve the set objectives: training 500 employees across different government entities and forming a community of 3.000 AI experts (Republic of Azerbaijan, 2025).

Another related challenge is that training content is frequently not aligned with the needs of frontline transport workers. Many programmes emphasise abstract AI concepts and general-purpose programming rather than job-specific practical competencies (Bedarkar, Kuknor and Gopalkrishnan, 2025).

How policymakers can address these challenges

To help workers overcome physical and social opportunity barriers, public authorities must help reshape the training ecosystem in a manner that ensures high-quality, relevant and accessible learning opportunities for all transport workers, regardless of their geographic location, role or educational background.

Enablement: Provide relevant digital training options for all, leveraging AI-enhanced learning technologies

As previously mentioned, most workers will not need specialised knowledge of how AI systems function, but rather, they will need to improve complementary skills in management and business processes, such as project management and interpersonal skills (Green, 2024). For most occupations, the priority is a broad understanding of AI and its relevance to day-to-day tasks (OECD, 2025g). This underscores the need for job-specific training that focuses on practical skills and not on abstract technical AI content.

The first step to ensuring training relevance may be to invest in the staff that designs and delivers training, namely the trainers. Instructors must first understand how AI and digital systems reshape workers' tasks: "training the trainers" is essential for delivering high-quality job-specific AI training.

To address geographic barriers remote workers face, public authorities can prioritise and subsidise the development of digital training or hybrid education programmes. Since in-person education is associated with more engagement and better retention, in-person or hybrid training should be favoured when possible (Qin, 2025). Transport authorities can expand access to high-quality learning by ensuring that digital training is available in formats that fit the realities of transport workers. To address unstable Internet connection in rural areas, training platforms should include an offline functionality, allowing workers to download training modules in advance and complete them without continuous Internet access.

In addition, public authorities could harness the potential of AI-powered learning technologies to personalise and enhance training effectiveness. Using AI, training programmes can be personalised in various ways: it can be designed to be adaptive by adjusting content difficulty and learning pace to individual progress, answer questions and offer immediate feedback, and even provide simulations of equipment operation. These tools support the development of cognitive skills, such as critical thinking and situation awareness, through repeated (simulated) action as well as develop social skills by modelling customer interaction. Moreover, AI can contribute to the development process of training by identifying skills gaps and matching these to available or new training methods (OECD, 2023).

Environmental restructuring: Prioritise support for workers most vulnerable to AI displacement

Transport occupations face a particularly high exposure to automation. On average, 18.5% of skills in this group are identified as highly automatable (compared with 12% across all occupations). On the other hand, the share of bottleneck skills, i.e. skills that cannot yet be automated (e.g. cognitive, social skills, critical thinking, etc.), is significantly lower (3.7% versus 15.6%). This means that many roles in the sector are likely to be exposed to changes in the AI era (ITF, 2023).

Given limited resources available for training, public authorities should focus on helping workers most vulnerable to displacement adapt through upskilling. First, this requires a sector-wide assessment of occupations at the highest risk of replacement. In transport, high-risk categories commonly include professional drivers, warehouse workers and administrative staff. By contrast, roles involving service, management and planning rely more on bottleneck skills (ITF, 2023; OECD, 2025g). A detailed mapping of skills according to their exposure to automation and their importance for the transport sector is provided in Annex C. This map helps visualise which skills should be the focus of targeted training, based on whether they are both in demand and highly automatable (or in demand and hard to automate).

There are also discrepancies related to socio-demographic factors: older workers are frequently perceived by employers as less willing or able to adapt to new technologies, which might reduce investment in their training, creating a self-fulfilling barrier (ITF, 2023). However, older workers' longer tenure and often more secure contracts mean they may in fact be less concerned about job loss where AI is introduced (ITF, 2023).

Finally, workers whose tasks are complemented rather than replaced by automation tend to have higher motivation to engage in AI-related further learning (Acemoglu et al., 2022). Therefore, transport authorities should try to identify such roles and encourage workers with strong interpersonal, problem-solving or technical skills into roles where these capabilities complement AI systems. For example, experienced drivers with strong customer-interaction skills could transition into roles that are customer facing at stations or in service centres.

Training: Expand apprenticeships and training opportunities

While adult apprenticeships can yield substantial, lasting earnings gains, outcomes often depend on addressing access barriers (Bratsberg, Nyen and Raaum, 2020). On-the-job learning has the greatest impact when workers have a chance to practice skills in actual operational contexts, especially when this is supported by clear training plans (Sung and Choi, 2014). Apprenticeships can be particularly valuable in new and emerging roles, such as automated fleet technician, AI-assisted logistics co-ordinator or predictive maintenance specialist.

Apprenticeships can improve social opportunity by strengthening employer commitments to training through designated mentors. By providing wage subsidies covering part of the apprentice's pay, public authorities can encourage employer participation, with higher support rates allocated for smaller companies.

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Annex A. Lists of Roundtable participants and observers

Affiliations at the time of the Roundtable

Audur ARNADOTTIR, Head of Traffic and Road Safety, Icelandic Road and Coastal Administration, Iceland

Salima BENHAMOU, Cheffe de projet, France Stratégie, France

Maruša BENKIC, Innovation and Policy Officer, Confederation of Organisations in Road Transport Enforcement (CORTE), Belgium

Emil BERLIN, Partnership and Governance Officer, ERTICO, Belgium

Stijn BROECKE, Senior Economist, OECD, France

Charlotte BYRNE, Researcher, Panteia, The Netherlands

Neil CHAUDHRY, Associate Administrator for Planning and Analytics, Department of Transportation, United States of America

Martin CLARKE, Project Manager, Panteia, The Netherlands

Camille COMBE, Policy Analyst – Innovation and Foresight, International Transport Forum, France

Giacomo DAMIOLI, Senior Research Fellow, University of Strasbourg, France

Albane DE CROMBRUGGHE, Policy Officer, SPF Mobilités et Transport, Belgium

Eric DIMNET, Deputy Head of Division, Directorate-General for Infrastructure, Transport and Mobility, France

Ellen DURST, Policy Officer, European Commission, Belgium

Stefan FLÜGEL, Chief Research Economist, Institute of Transport Economics, Oslo (TØI), Norway

Philip FREEMAN, Policy Advisor to the General Secretary, European Transport Workers' Federation, Belgium

Victor GEKARA, Professor of Logistics and Supply Chains, RMIT University, Australia

Patrick GRASSL, Advisor, Austrian Federal Ministry for Climate Action, Environment, Energy, Mobility, Innovation and Technology, Austria

Gabriele GRIMM, Deputy Research Commissioner, German Federal Ministry of Digital and Transport, Germany

Micah HIMMEL, Senior Advisor, Department of Transportation, United States of America

Patrik HLAVATY, Transport Analyst- Transport modelling, Ministry of Transport, Slovakia

Pedro HOMEM DE GOUVEIA, Project Manager, POLIS Network, Belgium

Haeun (Hailee) IM, International Cooperation Team Manager, Kakao Mobility, Republic of South Korea

Igor KABASHKIN, Professor, Transport and Telecommunication Institute, Latvia

Margarita KALAMOVA, Economist, OECD, France

Cristina LAZANU, Counsellor, Ministry of Transport and Infrastructure, Romania

Benoît LEBOT, Counsellor, French Ministry of the Ecological Transition, France

Luís Miguel MARTINS, Transport Public Service Fund Coordinator, Institute of Mobility and Transport, Portugal

Orla MCCARTHY, Policy Analyst, International Transport Forum, France

Mike MOON, Head of the Future Platform Economy Research Institute, Kakao Mobility, Republic of South Korea

Kristin MÜHL, Scientific Officer, DZSF- German Centre for Rail Traffic Research, Germany

Yu MURATA, Senior Research Officer, Policy Research Institute for Land, Infrastructure, Transport and Tourism (PRILIT), Japan

Natalia OLIARI, National Director of Road Safety Observatory, National Road Safety Agency, Argentina

Brigitte OLLIER, Senior Advisor on Social Affairs, UITP, Belgium

Sean PERRYMAN, Global Head of AI & Fairness Policy, Uber, United States of America

Cristina PRONELLO, Full Professor, Politecnico di Torino, Department of Environment, Land and Infrastructure Engineering, Italy

Christophe RAFENBERG, Project manager, Directorate-General for Infrastructure, Transport and Mobility-Transport Innovation Agency, France

Joshua RAYNER, Executive Director Skill Strategies, Skill Insight

Gustavo RINALDI, Director de Impacto Ambiental del Transporte, Secretary of Transport, Argentina

Lindsay ROBLES, Director, Transport Canada, Canada

Lea SAMEK, Economist, OECD, France

Haruki SAWAMURA, Research Officer, Policy Research Institute for Land, Infrastructure, Transport and Tourism (PRILIT), Japan

Jens-Uwe SCHRÖDER-HINRICHS, Vice-President, Strategic Initiative and Professor, World Maritime University (WMU), Sweden *(Chair)*

Christopher SCHUBERT, Counsellor, Permanent Mission to the OECD, Mexico

Antonios STATHOPOULOS, Professor, School of Civil Engineering, National Technical University of Athens, Greece

Maurizio TIRA, Professor, University of Brescia, Italy

Bera TOMMASI, Policy Officer, European Transport Workers' Federation, Belgium

Hajime TOZAKI, Visiting Research Officer, Policy Research Institute for Land, Infrastructure, Transport and Tourism (PRILIT), Japan

Vaida UBARTAITE, National expert, International Transport Forum

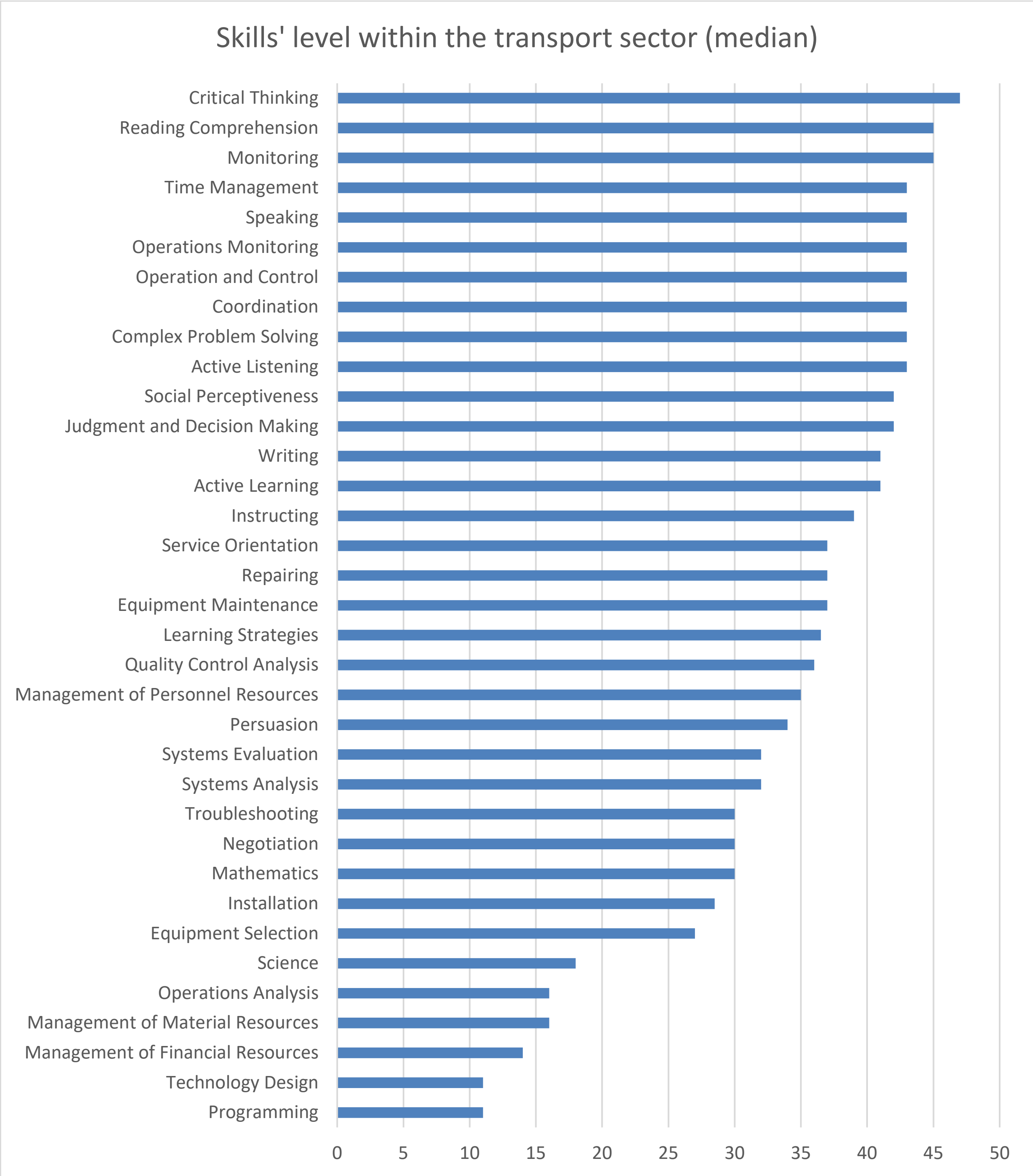
Agne VAITEKENAITE, Manager, Partnership development, ERTICO, Belgium

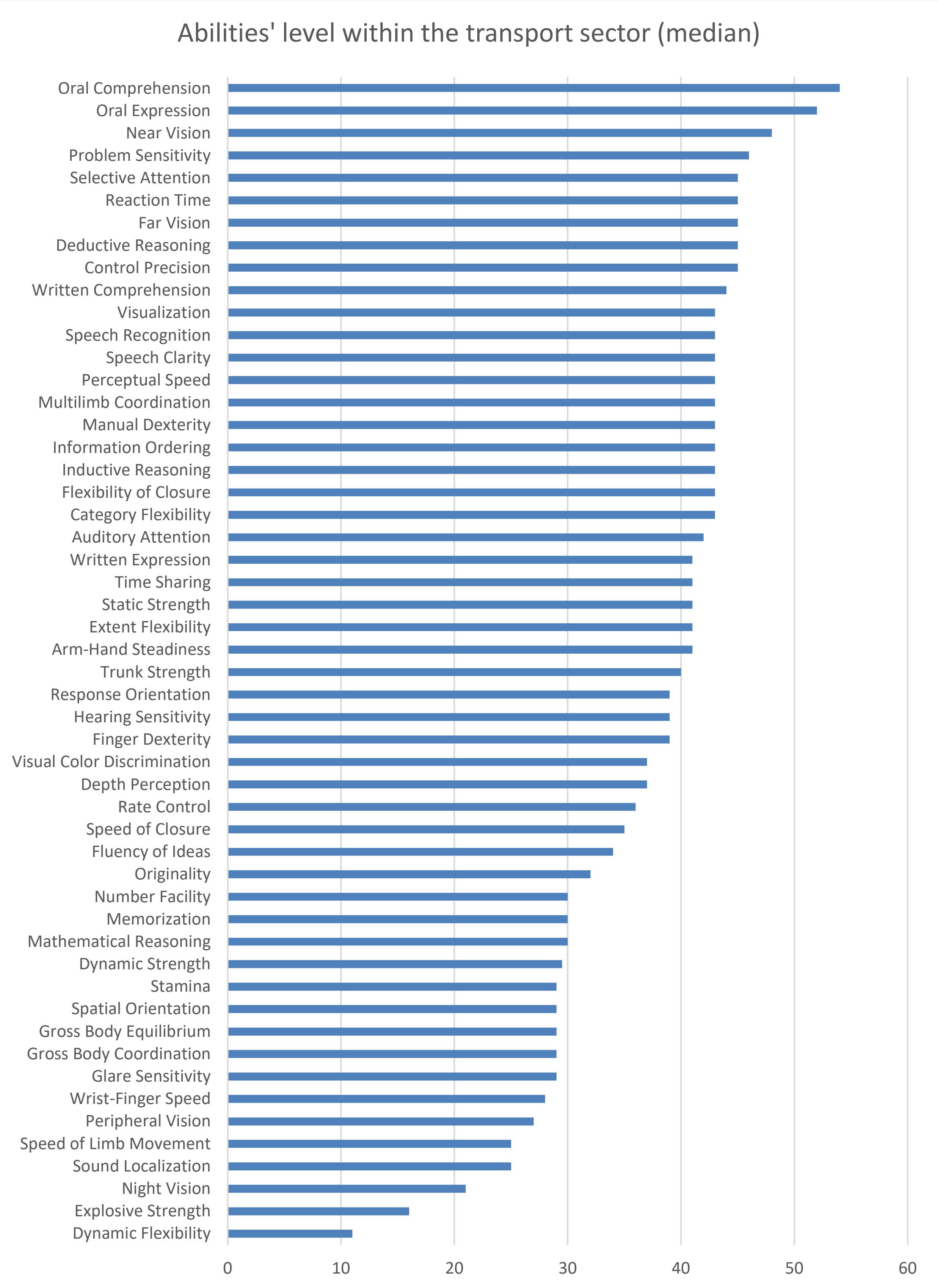
Paul WALSH, Chief Executive Officer, Industry Skills Australia, Australia

Anna WINKLE, Federal Motor Carrier Safety Administration, Attorney Advisor, Department of Transportation, United States of America

Mahdi ZARGAYOUNA, Researcher, Deputy Director of the GRETTIA Laboratory, Université Gustave Eiffel, France

Annex B. Skill and abilities levels in the transport sector




Abilities' level within the transport sector (median)
Oral Comprehension
Oral Expression
Near Vision
Problem Sensitivity
Selective Attention
Reaction Time
Far Vision
Deductive Reasoning
Control Precision
Written Comprehension
Visualization
Speech Recognition
Speech Clarity
Perceptual Speed
Multilimb Coordination
Manual Dexterity
Information Ordering
Inductive Reasoning
Flexibility of Closure
Category Flexibility
Auditory Attention
Written Expression
Time Sharing
Static Strength
Extent Flexibility
Arm-Hand Steadiness
Trunk Strength
Response Orientation
Hearing Sensitivity
Finger Dexterity
Visual Color Discrimination
Depth Perception
Rate Control
Speed of Closure
Fluency of Ideas
Originality
Number Facility
Memorization
Mathematical Reasoning
Dynamic Strength
Stamina
Spatial Orientation
Gross Body Equilibrium
Gross Body Coordination
Glare Sensitivity
Wrist-Finger Speed
Peripheral Vision
Speed of Limb Movement
Sound Localization
Night Vision
Explosive Strength
Dynamic Flexibility
0
10
20
30
40
50
60

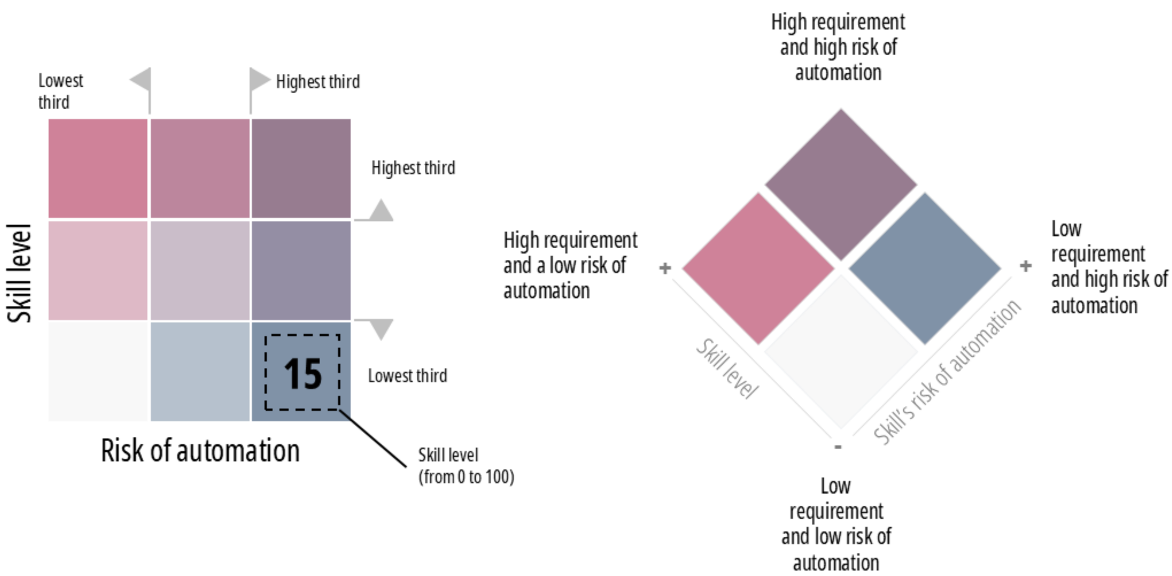
Annex C. Mapping of skills and abilities' level and risk of automation in the transport sector

Annex C presents the relative level and risk of automation of skills and abilities in the transport sector.

The numerical values in each cell represent the level of a specific skill or ability required for a particular occupation based on O*NET data. The skill or ability level reflects "*the degree, or point along a continuum, to which a particular descriptor is required or needed to perform the occupation*" (O*NET, n.d.)(O*NET, n.d.). "NA" means the data were not available; "NR" implies a given skill or ability is not relevant to the occupation considered.

The risk of automation is derived from the automatability index developed from data from the OECD Expert Survey on Skills and Abilities Automatability and provided in Figure 7. Automatability of skills and abilities.

Colours have been assigned to differentiate groups of skills and abilities based on their relative level and risk of automation. These groups are categorised into the lowest third, the middle third and the highest third for both skill level and risk of automation. The legend is provided below:



Annex C.1. Relative level and risk of automation of skills in air transport-related occupations

		Skill																																		
		Basic Skills										Complex	Digital	Resource Management Skills				Social Skills						Systems Skills			Technical Skills									
Domain	Jobs	Active Learning	Active Listening	Learning Strategies	Critical Thinking	Writing	Speaking	Monitoring	Science	Reading Comprehension	Mathematics	Complex Problem Solving	Programming	Management of Personnel	Management of Material	Management of Financial	Time Management	Negotiation	Social Perceptiveness	Service Orientation	Persuasion	Coordination	Instructing	Systems Analysis	Systems Evaluation	Judgment and Decision	Technology Design	Repairing	Operations Analysis	Installation	Troubleshooting	Equipment Selection	Equipment Maintenance	Quality Control Analysis	Operation and Control	Operations Monitoring
Air	Aircraft Cargo Handling Supervisors	50	66	63	69	53	66	66	13	56	50	53	16	69	28	19	66	38	56	47	44	63	53	50	44	60	19	25	19	3	35	22	25	41	44	44
	Aircraft Mechanics and Service Technicians	45	48	41	57	43	46	45	37	57	32	55	7	32	27	9	43	30	43	41	39	43	43	46	46	48	18	61	30	30	57	43	68	55	46	57
	Airfield Operations Specialists	46	57	45	55	46	55	59	11	57	30	46	5	43	25	11	43	43	43	43	41	57	45	43	45	46	13	NR	39	NR	16	NR	NR	34	39	41
	Airline Pilots, Copilots, and Flight Engineers	59	61	45	59	46	54	61	39	59	50	52	7	45	25	14	55	37	46	41	37	54	57	46	46	61	9	NR	29	NR	45	NR	18	43	80	70
	Aviation Inspectors	46	48	43	57	46	57	48	50	48	34	52	7	41	13	11	46	41	43	43	43	43	45	43	43	48	11	41	39	NR	46	37	41	54	45	57
	Avionics Technicians	45	46	37	54	45	43	46	41	50	30	50	13	37	16	9	46	32	43	37	39	45	41	45	45	46	16	57	30	41	57	43	57	52	36	52
	Baggage Porters and Bellhops	30	45	29	39	30	37	32	NR	37	27	30	NR	32	14	14	32	30	34	43	30	39	36	29	30	32	NR	11	NR	NR	25	7	11	23	30	30
	Commercial Pilots	57	59	50	57	43	54	57	39	59	41	52	7	43	14	11	43	36	43	41	43	50	48	43	43	54	7	16	14	NR	45	13	20	39	75	68
	Flight Attendants	43	46	32	52	41	54	48	7	50	27	37	5	32	16	14	43	39	46	52	41	46	41	27	27	41	11	NR	11	NR	23	NR	NR	30	21	30

Annex C.2. Relative level and risk of automation of abilities in air transport-related occupations

Ability – Cognitive abilities

Domain	Jobs	Originality	Written	Problem Sensitivity	Mathematical	Written Expression	Inductive	Oral Expression	Visualization	Fluency of Ideas	Oral	Speed of Closure	Deductive	Category Flexibility	Time Sharing	Flexibility of Closure	Perceptual Speed	Spatial Orientation	Information	Selective Attention	Memorization	Number Facility
Air	Aircraft Cargo Handling Supervisors	43	43	50	41	41	43	55	52	43	55	43	45	43	45	45	45	29	45	50	34	43
	Aircraft Mechanics and Service Technicians	41	59	57	39	45	55	54	57	43	55	43	55	52	41	52	52	29	57	45	36	32
	Airfield Operations Specialists	43	57	61	34	54	50	57	43	43	57	39	57	45	43	45	45	34	54	48	30	30
	Airline Pilots, Copilots, and Flight Engineers	43	59	71	45	46	61	63	57	45	68	57	63	48	61	59	61	66	59	59	45	52
	Aviation Inspectors	41	57	63	36	55	57	57	46	41	57	45	57	46	43	46	48	29	52	45	34	34
	Avionics Technicians	39	61	55	32	54	54	55	55	43	59	32	55	43	37	46	41	13	55	46	34	30
	Baggage Porters and Bellhops	29	41	39	23	30	30	52	30	30	45	29	32	32	41	30	34	32	36	41	30	21
	Commercial Pilots	43	57	70	43	54	57	59	48	45	61	50	57	45	57	55	57	55	57	57	37	39
	Flight Attendants	30	43	55	27	41	46	57	29	34	57	39	52	43	41	39	45	NR	43	45	29	29

Ability – Physical abilities

Domain	Jobs	Gross Body	Gross Body	Trunk Strength	Dynamic Flexibility	Extent Flexibility	Explosive Strength	Stamina	Dynamic Strength	Static Strength
Air	Aircraft Cargo Handling Supervisors	27	32	43	13	45	16	36	32	54
	Aircraft Mechanics and Service Technicians	27	30	43	5	48	NR	32	30	43
	Airfield Operations Specialists	16	16	25	NR	18	5	13	14	16
	Airline Pilots, Copilots, and Flight Engineers	27	11	20	NR	36	7	9	13	30
	Aviation Inspectors	20	27	32	NR	34	9	25	21	29
	Avionics Technicians	21	21	32	NR	34	9	20	25	30
	Baggage Porters and Bellhops	29	39	45	NR	41	18	41	37	54
	Commercial Pilots	23	25	32	NR	30	14	21	27	30
	Flight Attendants	45	39	43	NR	45	13	37	30	41

Ability – Psychomotor abilities

Domain	Jobs	Rate Control	Finger Dexterity	Manual Dexterity	Multilimb	Response	Arm-Hand	Speed of Limb	Control Precision	Reaction Time	Wrist-Finger Speed
Air	Aircraft Cargo Handling Supervisors	36	39	45	43	37	37	29	43	43	29
	Aircraft Mechanics and Service Technicians	41	59	59	55	43	54	30	57	46	30
	Airfield Operations Specialists	14	30	32	30	30	29	9	41	29	14
	Airline Pilots, Copilots, and Flight Engineers	71	45	46	61	80	54	39	64	71	39
	Aviation Inspectors	29	43	43	41	36	43	13	46	36	21
	Avionics Technicians	21	54	46	43	20	45	NR	46	27	23
	Baggage Porters and Bellhops	21	32	36	39	29	32	18	39	25	16
	Commercial Pilots	57	43	45	59	66	45	23	64	59	30
	Flight Attendants	11	39	39	37	21	39	27	27	30	7

Ability – Sensory abilities

Domain	Jobs	Glare Sensitivity	Speech Recognition	Auditory Attention	Night Vision	Speech Clarity	Depth Perception	Far Vision	Peripheral Vision	Hearing Sensitivity	Sound Localization	Visual Color	Near Vision
Air	Aircraft Cargo Handling Supervisors	32	43	46	18	46	43	46	29	39	25	41	46
	Aircraft Mechanics and Service Technicians	27	43	45	27	43	43	45	18	48	29	55	59
	Airfield Operations Specialists	30	45	46	29	43	37	57	30	34	21	39	54
	Airline Pilots, Copilots, and Flight Engineers	61	57	57	55	55	63	77	57	57	41	48	63
	Aviation Inspectors	27	46	46	20	45	37	48	20	45	29	46	57
	Avionics Technicians	11	43	39	9	41	32	43	9	41	13	50	59
	Baggage Porters and Bellhops	18	43	37	14	43	30	39	18	30	20	29	45
	Commercial Pilots	50	52	46	43	55	59	68	45	45	37	46	55
	Flight Attendants	9	55	52	NR	57	27	45	NR	30	NR	37	46

Annex C.3. Relative level and risk of automation of skills in land transport-related occupations

		Skill																																		
		Basic Skills										Complex	Digital	Resource Management Skills				Social Skills						Systems Skills			Technical Skills									
Domain	Jobs	Active Learning	Active Listening	Learning Strategies	Critical Thinking	Writing	Speaking	Monitoring	Science	Reading Comprehension	Mathematics	Complex Problem Solving	Programming	Management of Personnel	Management of Material	Management of Financial	Time Management	Negotiation	Social Perceptiveness	Service Orientation	Persuasion	Coordination	Instructing	Systems Analysis	Systems Evaluation	Judgment and Decision	Technology Design	Repairing	Operations Analysis	Installation	Troubleshooting	Equipment Selection	Equipment Maintenance	Quality Control Analysis	Operation and Control	Operations Monitoring
Land	Bridge and Lock Tenders	30	39	30	43	41	41	43	NR	34	27	39	NR	30	NR	NR	37	30	32	37	32	43	37	14	21	37	NR	18	NR	NR	29	11	20	32	43	43
	Bus and Truck Mechanics and Diesel Engine Specialists	41	43	37	48	39	43	43	18	41	29	43	16	29	13	13	41	29	39	30	32	41	39	36	34	43	13	55	16	27	54	43	48	46	45	46
	Bus Drivers, Transit and Intercity	29	39	25	39	30	32	36	NR	34	25	23	NR	21	11	14	39	23	34	37	25	36	21	16	16	34	11	13	NR	NR	25	5	14	25	45	43
	Packers and Packagers, Hand	14	29	16	29	27	29	30	NR	29	18	25	5	18	9	NR	27	9	27	29	9	30	14	14	14	27	NR	NR	NR	NR	11	9	5	27	23	21
	Passenger Attendants	36	46	21	46	34	41	46	NR	41	20	34	5	29	5	5	34	30	45	54	39	43	32	21	25	32	5	NR	5	NR	23	NR	NR	29	25	34
	Conveyor Operators and Tenders	37	43	29	41	39	41	45	21	41	27	39	NR	36	16	5	41	30	37	32	30	41	39	37	36	39	14	36	25	NR	39	27	37	37	55	57
	Couriers and Messengers	32	41	27	37	39	37	30	NR	41	30	34	NR	20	9	11	39	25	34	37	25	34	23	27	23	29	5	NR	5	NR	21	NR	14	20	32	30
	Dispatchers, Except Police, Fire, and Ambulance	41	55	39	54	41	55	46	NR	46	29	43	5	39	20	14	45	39	43	41	41	52	36	39	39	41	11	NR	11	NR	9	NR	NR	27	NR	25
	Electrical and Electronics Installers and Repairers, Transportation Equipment	34	43	32	43	43	43	43	32	45	32	43	11	32	14	16	45	30	43	32	39	43	36	32	34	41	20	45	23	34	46	32	43	46	36	45
	First-Line Supervisors of Helpers, Laborers, and Material Movers, Hand	43	54	46	52	45	54	50	7	50	30	43	NR	54	34	32	52	43	48	39	45	54	43	39	41	43	9	13	23	NR	20	16	13	34	30	39
	First-Line Supervisors of Material-Moving Machine and Vehicle Operators	45	55	45	52	52	55	54	NR	54	32	48	NR	54	32	20	55	41	50	43	43	55	45	45	43	46	5	29	36	NR	29	13	29	34	32	36
	Freight Forwarders	45	48	41	48	45	46	45	NR	46	45	45	11	37	29	29	45	48	46	45	46	48	41	45	43	43	11	9	11	NR	13	11	11	13	11	30
	Heavy and Tractor-Trailer Truck Drivers	30	43	25	41	37	41	43	NR	43	27	36	NR	25	23	20	43	29	34	29	25	32	25	29	27	39	5	39	13	14	41	27	39	36	52	45
	Industrial Truck and Tractor Operators	27	36	25	32	30	29	37	NR	36	27	29	NR	21	13	13	32	23	29	25	25	43	29	25	25	30	9	29	9	NR	36	21	37	27	43	41
	Light Truck Drivers	29	41	23	39	36	41	39	NR	43	30	32	NR	23	13	7	37	21	34	29	25	29	23	27	25	29	NR	29	9	NR	29	14	30	27	41	36
	Locomotive Engineers	43	46	43	45	41	43	54	5	50	37	43	NR	36	13	13	39	25	37	27	25	43	37	32	30	43	NR	20	16	NR	37	11	20	43	59	57
	Machine Feeders and Offbearers	29	37	25	37	29	37	41	NR	41	23	30	NR	20	13	11	36	23	30	27	27	29	27	13	20	32	NR	18	NR	NR	29	13	18	36	36	48
	Rail Car Repairers	39	43	32	48	39	34	39	14	39	30	37	NR	32	14	13	43	30	32	30	30	37	32	32	34	39	14	57	16	36	54	34	46	46	43	43
	Rail Yard Engineers, Dinkey Operators, and Hostlers	39	43	36	43	36	45	45	7	45	29	45	NR	34	13	11	43	25	30	29	25	46	41	30	32	41	NR	43	5	13	43	29	37	43	52	52
	Railroad Conductors and Yardmasters	43	45	39	52	41	45	57	7	46	37	48	7	50	13	11	50	30	43	37	43	55	43	43	43	43	5	NR	23	NR	30	NR	NR	43	45	45
	Rail-Track Laying and Maintenance Equipment Operators	34	39	32	43	30	32	41	NR	32	29	34	NR	30	14	11	39	25	29	27	27	45	37	30	29	39	11	43	11	7	43	32	43	43	45	46
	Recycling and Reclamation Workers	32	41	29	39	36	34	39	NR	41	21	34	NR	29	16	9	36	21	37	32	21	30	29	21	21	30	11	34	NR	NR	34	27	37	32	39	39
	Recycling Coordinators	45	45	43	50	45	48	50	NR	50	39	39	7	50	34	34	52	43	45	41	46	46	41	39	41	45	13	NR	16	NR	16	NR	NR	30	37	39
	Railroad Brake, Signal, and Switch Operators and Locomotive Firers	36	41	36	41	37	37	45	NR	43	25	41	NR	34	14	11	37	30	37	32	34	45	36	29	29	34	NR	16	NR	NR	29	11	NA	32	46	48
	Reservation and Transportation Ticket Agents and Travel Clerks	43	57	37	52	43	46	41	NR	45	36	43	13	29	7	5	43	41	45	54	43	43	39	32	32	43	7	NR	14	NR	7	NR	NR	16	7	23
	Signal and Track Switch Repairers	43	43	39	48	43	36	45	13	41	32	43	13	30	13	11	43	30	30	30	30	39	39	32	32	41	9	55	NR	37	57	39	55	55	43	54
	Stockers and Order Fillers	30	43	30	34	37	39	37	NR	43	25	32	11	32	20	13	36	25	37	36	27	37	27	27	25	32	13	NR	9	NR	21	NR	NR	23	29	25
	Transit and Railroad Police	43	46	46	48	43	55	50	NR	46	29	43	11	41	16	16	45	45	46	43	48	46	43	39	32	45	9	NR	25	NR	21	NR	NR	23	32	32
	Transportation Inspectors	39	50	37	50	50	50	48	7	52	37	46	11	43	27	25	45	34	43	41	37	45	37	39	41	46	11	NR	NR	NR	25	NR	NR	36	34	37
	Transportation Vehicle, Equipment and Systems Inspectors, Except Aviation	29	41	27	41	39	41	41	34	45	25	32	NR	29	5	NR	41	27	39	29	30	39	29	21	25	36	13	37	13	NR	41	29	41	46	43	45
	Transportation, Storage, and Distribution Managers	52	55	46	52	52	54	54	NR	54	41	52	16	48	43	NA	54	52	48	45	52	55	48	50	50	50	16	NR	NA	NR	16	NR	NR	32	23	36

Annex C.4. Relative level and risk of automation of abilities in land transport-related occupations

Ability

Cognitive abilities

Domain	Jobs	Originality	Written	Problem Sensitivity	Mathematical	Written Expression	Inductive	Oral Expression	Visualization	Fluency of Ideas	Oral	Speed of Closure	Deductive	Category Flexibility	Time Sharing	Flexibility of Closure	Perceptual Speed	Spatial Orientation	Information	Selective Attention	Memorization	Number Facility
Land	Bridge and Lock Tenders	30	41	41	27	41	39	43	29	30	45	34	41	41	41	39	41	25	43	45	32	29
Land	Bus and Truck Mechanics and Diesel Engine Specialists	39	45	46	25	37	48	45	54	41	54	32	48	43	43	45	43	25	48	43	30	30
Land	Bus Drivers, Transit and Intercity	25	36	43	16	29	32	43	32	23	41	30	32	29	46	32	41	41	37	46	29	18
Land	Packers and Packagers, Hand	9	29	36	16	27	29	41	27	13	43	21	30	30	25	29	30	16	30	30	18	20
Land	Passenger Attendants	30	43	46	21	34	41	57	29	30	52	29	41	41	39	36	36	14	37	39	29	23
Land	Conveyor Operators and Tenders	30	41	45	25	41	43	48	43	32	50	32	43	43	36	41	46	20	50	45	29	25
Land	Couriers and Messengers	27	43	37	23	34	32	43	30	25	45	29	41	39	41	30	37	32	43	37	27	27
Land	Dispatchers, Except Police, Fire, and Ambulance	39	46	46	32	46	45	57	30	39	57	41	52	43	39	37	39	NR	43	45	36	32
Land	Electrical and Electronics Installers and Repairers, Transportation Equipment	32	43	46	30	43	43	46	45	34	54	30	43	45	34	43	43	14	45	41	25	30
Land	First-Line Supervisors of Helpers, Laborers, and Material Movers, Hand	43	54	52	30	46	45	57	43	43	57	30	54	43	41	37	34	20	48	43	29	34
Land	First-Line Supervisors of Material-Moving Machine and Vehicle Operators	45	55	54	39	54	43	57	43	43	57	39	54	43	43	43	41	25	50	43	30	39
Land	Freight Forwarders	39	54	46	43	50	43	55	41	43	55	39	54	45	41	41	43	13	43	37	37	43
Land	Heavy and Tractor-Trailer Truck Drivers	25	43	43	27	30	41	43	43	29	43	32	43	43	43	39	41	50	41	45	27	29
Land	Industrial Truck and Tractor Operators	23	30	43	29	29	32	41	43	29	45	25	43	34	39	34	43	43	37	45	21	32
Land	Light Truck Drivers	27	43	41	29	32	37	52	39	29	43	29	41	37	41	30	37	45	41	41	25	29
Land	Locomotive Engineers	29	45	48	32	39	45	55	43	29	55	41	45	39	50	50	54	45	46	57	32	36
Land	Machine Feeders and Offbearers	25	43	39	25	39	39	43	37	27	43	21	39	41	36	41	43	7	41	41	25	29
Land	Rail Car Repairers	30	41	46	30	34	43	43	55	30	43	37	43	43	36	46	45	30	43	45	30	30
Land	Rail Yard Engineers, Dinkey Operators, and Hostlers	29	45	59	29	37	43	54	46	30	55	39	45	41	43	45	45	43	43	46	30	29
Land	Railroad Conductors and Yardmasters	39	43	54	30	43	45	57	48	39	57	34	54	45	41	43	45	32	54	46	29	32
Land	Rail-Track Laying and Maintenance Equipment Operators	30	39	43	21	32	41	43	50	30	46	34	43	37	41	48	45	34	41	45	27	27
Land	Recycling and Reclamation Workers	27	39	36	20	37	36	41	34	30	41	29	36	43	37	39	39	30	41	39	27	21
Land	Recycling Coordinators	36	46	43	36	46	45	52	30	41	54	30	46	41	34	37	34	21	45	37	29	37
Land	Railroad Brake, Signal, and Switch Operators and Locomotive Firers	36	46	45	25	37	43	46	37	34	52	32	45	37	45	43	45	32	43	43	25	29
Land	Reservation and Transportation Ticket Agents and Travel Clerks	39	48	43	29	43	43	57	29	41	52	34	45	43	39	37	32	NR	43	41	34	34
Land	Signal and Track Switch Repairers	29	43	48	36	43	48	43	52	34	54	39	54	43	43	52	46	39	43	45	39	30
Land	Stockers and Order Fillers	30	41	41	21	34	36	45	37	32	45	27	37	41	32	32	37	23	39	37	29	29
Land	Transit and Railroad Police	43	46	57	29	46	55	57	41	43	57	45	55	43	39	48	43	39	43	46	32	30
Land	Transportation Inspectors	39	54	57	41	52	50	57	43	43	57	39	50	48	36	48	45	34	48	41	37	39
Land	Transportation Vehicle, Equipment and Systems Inspectors, Except Aviation	29	43	45	25	39	43	46	39	30	52	32	43	41	37	43	41	27	43	41	27	25
Land	Transportation, Storage, and Distribution Managers	46	55	54	41	54	50	59	36	50	54	41	54	48	39	43	41	20	48	43	36	43

Physical abilities

Domain	Jobs	Gross Body	Gross Body	Trunk Strength	Dynamic Flexibility	Extent Flexibility	Explosive Strength	Stamina	Dynamic Strength	Static Strength
Land	Bridge and Lock Tenders	29	29	34	NR	29	14	25	29	32
Land	Bus and Truck Mechanics and Diesel Engine Specialists	34	30	45	NR	55	18	39	32	45
Land	Bus Drivers, Transit and Intercity	11	21	30	NR	29	9	13	18	27
Land	Packers and Packagers, Hand	14	29	45	7	41	5	32	30	43
Land	Passenger Attendants	30	34	39	NR	30	27	27	25	29
Land	Conveyor Operators and Tenders	29	29	43	NR	43	20	25	30	43
Land	Couriers and Messengers	25	30	41	11	39	11	37	30	37
Land	Dispatchers, Except Police, Fire, and Ambulance	NR	NR	16	NR	NR	NR	NR	NR	NR
Land	Electrical and Electronics Installers and Repairers, Transportation Equipment	27	30	43	NR	48	16	27	21	30
Land	First-Line Supervisors of Helpers, Laborers, and Material Movers, Hand	20	29	41	7	34	16	29	29	34
Land	First-Line Supervisors of Material-Moving Machine and Vehicle Operators	13	27	32	NR	18	NR	23	9	30
Land	Freight Forwarders	9	7	16	NR	14	11	9	7	13
Land	Heavy and Tractor-Trailer Truck Drivers	29	27	39	13	39	16	30	34	48
Land	Industrial Truck and Tractor Operators	29	29	43	13	45	18	32	36	52
Land	Light Truck Drivers	18	32	45	5	43	7	37	32	52
Land	Locomotive Engineers	21	29	36	NR	30	7	21	29	37
Land	Machine Feeders and Offbearers	27	30	41	NR	39	16	29	30	43
Land	Rail Car Repairers	43	41	54	NR	50	18	43	41	52
Land	Rail Yard Engineers, Dinkey Operators, and Hostlers	39	39	43	NR	45	13	30	32	45
Land	Railroad Conductors and Yardmasters	36	34	37	NR	39	NR	34	23	36
Land	Rail-Track Laying and Maintenance Equipment Operators	34	43	50	NR	46	20	41	46	54
Land	Recycling and Reclamation Workers	27	37	43	NR	41	NR	34	29	43
Land	Recycling Coordinators	NR	NR	29	NR	NR	NR	NR	NR	25
Land	Railroad Brake, Signal, and Switch Operators and Locomotive Firers	41	36	46	NR	45	34	36	37	41
Land	Reservation and Transportation Ticket Agents and Travel Clerks	14	21	30	NR	14	NR	20	21	34
Land	Signal and Track Switch Repairers	32	30	45	NR	41	11	34	32	41
Land	Stockers and Order Fillers	34	32	41	13	48	27	32	32	41
Land	Transit and Railroad Police	32	39	46	NR	36	45	43	41	45
Land	Transportation Inspectors	25	25	36	NR	30	20	23	21	25
Land	Transportation Vehicle, Equipment and Systems Inspectors, Except Aviation	20	25	37	NR	45	NR	27	18	30
Land	Transportation, Storage, and Distribution Managers	NR	NR	27	NR	NR	NR	NR	7	NR

Psychomotor abilities

Domain	Jobs	Rate Control	Finger Dexterity	Manual Dexterity	Multilimb	Response	Arm-Hand	Speed of Limb	Control Precision	Reaction Time	Wrist-Finger Speed
Land	Bridge and Lock Tenders	37	37	36	43	37	39	27	46	45	29
Land	Bus and Truck Mechanics and Diesel Engine Specialists	32	52	46	50	39	46	25	54	43	32
Land	Bus Drivers, Transit and Intercity	46	30	30	50	55	41	21	48	54	16
Land	Packers and Packagers, Hand	21	37	45	39	16	32	29	32	27	23
Land	Passenger Attendants	11	27	29	30	27	30	16	30	21	11
Land	Conveyor Operators and Tenders	45	43	45	50	41	45	18	50	45	21
Land	Couriers and Messengers	34	36	39	45	45	37	23	43	32	14
Land	Dispatchers, Except Police, Fire, and Ambulance	NR	30	20	NR	NR	16	NR	27	NR	9
Land	Electrical and Electronics Installers and Repairers, Transportation Equipment	20	50	45	43	20	50	5	45	29	20
Land	First-Line Supervisors of Helpers, Laborers, and Material Movers, Hand	30	39	43	32	27	37	9	37	30	13
Land	First-Line Supervisors of Material-Moving Machine and Vehicle Operators	29	34	34	37	30	39	11	34	30	21
Land	Freight Forwarders	11	25	14	13	9	16	NR	16	13	11
Land	Heavy and Tractor-Trailer Truck Drivers	57	39	43	57	57	43	37	55	57	39
Land	Industrial Truck and Tractor Operators	46	43	43	57	46	41	25	57	50	29
Land	Light Truck Drivers	41	32	41	46	43	37	25	43	43	23
Land	Locomotive Engineers	54	43	43	55	57	43	32	57	63	36
Land	Machine Feeders and Offbearers	43	41	43	39	29	46	23	54	46	32
Land	Rail Car Repairers	34	54	54	54	39	50	32	54	54	37
Land	Rail Yard Engineers, Dinkey Operators, and Hostlers	43	41	43	54	54	43	36	54	55	32
Land	Railroad Conductors and Yardmasters	41	39	37	41	37	41	29	45	50	25
Land	Rail-Track Laying and Maintenance Equipment Operators	45	41	45	57	46	43	39	57	52	34
Land	Recycling and Reclamation Workers	41	45	48	54	39	46	41	52	46	36
Land	Recycling Coordinators	18	34	27	39	29	30	16	36	27	18
Land	Railroad Brake, Signal, and Switch Operators and Locomotive Firers	46	39	43	48	46	41	13	52	54	30
Land	Reservation and Transportation Ticket Agents and Travel Clerks	20	36	29	29	5	30	NR	29	20	7
Land	Signal and Track Switch Repairers	32	54	48	45	41	46	27	54	46	29
Land	Stockers and Order Fillers	25	36	41	43	25	39	NR	37	21	21
Land	Transit and Railroad Police	36	36	39	43	45	41	30	39	45	30
Land	Transportation Inspectors	20	7	11	29	30	27	NR	25	29	25
Land	Transportation Vehicle, Equipment and Systems Inspectors, Except Aviation	32	43	41	39	30	45	13	43	34	25
Land	Transportation, Storage, and Distribution Managers	13	18	14	11	13	16	NR	16	13	NA

Sensory abilities

Domain	Jobs	Glare Sensitivity	Speech Recognition	Auditory Attention	Night Vision	Speech Clarity	Depth Perception	Far Vision	Peripheral Vision	Hearing Sensitivity	Sound Localization	Visual Color	Near Vision
Land	Bridge and Lock Tenders	43	43	43	29	45	41	54	30	43	30	36	43
Land	Bus and Truck Mechanics and Diesel Engine Specialists	30	41	45	25	43	43	45	25	55	37	46	57
Land	Bus Drivers, Transit and Intercity	39	41	43	39	41	41	52	43	39	30	36	41
Land	Packers and Packagers, Hand	7	30	27	7	29	29	29	13	18	7	27	45
Land	Passenger Attendants	13	48	34	14	50	27	37	14	32	11	27	43
Land	Conveyor Operators and Tenders	32	41	43	20	41	45	45	20	43	21	39	45
Land	Couriers and Messengers	32	50	34	20	41	37	39	27	29	29	30	46
Land	Dispatchers, Except Police, Fire, and Ambulance	NR	59	32	NR	57	11	41	NR	29	NR	21	54
Land	Electrical and Electronics Installers and Repairers, Transportation Equipment	14	43	30	13	43	34	43	13	32	14	48	57
Land	First-Line Supervisors of Helpers, Laborers, and Material Movers, Hand	20	48	37	13	45	29	43	20	27	18	27	45
Land	First-Line Supervisors of Material-Moving Machine and Vehicle Operators	11	43	34	9	45	37	43	18	30	21	34	48
Land	Freight Forwarders	7	48	30	7	43	18	41	7	29	7	32	48
Land	Heavy and Tractor-Trailer Truck Drivers	41	41	45	41	41	50	55	43	43	41	36	45
Land	Industrial Truck and Tractor Operators	25	32	45	21	32	55	48	43	39	29	37	43
Land	Light Truck Drivers	30	43	32	32	41	41	48	32	34	29	36	43
Land	Locomotive Engineers	41	43	57	36	43	50	64	39	41	30	41	48
Land	Machine Feeders and Offbearers	5	39	39	5	39	37	39	5	36	5	30	45
Land	Rail Car Repairers	30	34	46	25	36	43	45	27	43	29	54	54
Land	Rail Yard Engineers, Dinkey Operators, and Hostlers	41	45	50	25	43	45	59	36	41	27	45	48
Land	Railroad Conductors and Yardmasters	37	45	55	25	50	43	55	30	41	23	39	50
Land	Rail-Track Laying and Maintenance Equipment Operators	41	32	45	25	34	48	54	29	41	20	37	43
Land	Recycling and Reclamation Workers	25	41	32	23	37	43	41	23	32	21	37	48
Land	Recycling Coordinators	16	45	34	16	46	30	39	13	25	11	29	43
Land	Railroad Brake, Signal, and Switch Operators and Locomotive Firers	34	43	NA	36	41	39	54	27	41	27	45	50
Land	Reservation and Transportation Ticket Agents and Travel Clerks	11	54	39	NR	57	9	41	NR	27	NR	29	54
Land	Signal and Track Switch Repairers	36	41	43	29	37	41	50	30	43	30	54	52
Land	Stockers and Order Fillers	18	41	32	14	39	34	43	18	27	18	32	46
Land	Transit and Railroad Police	37	46	41	43	46	41	55	37	39	30	39	46
Land	Transportation Inspectors	23	50	NA	18	45	34	46	27	29	21	36	48
Land	Transportation Vehicle, Equipment and Systems Inspectors, Except Aviation	25	41	39	23	43	37	39	25	41	18	39	55
Land	Transportation, Storage, and Distribution Managers	13	48	NA	16	50	21	43	16	27	13	32	50

Annex C.5. Relative level and risk of automation of skills in waterborne and transversal transport-related occupations

		Skill																																		
		Basic Skills										Complex	Digital	Resource Management Skills				Social Skills						Systems Skills			Technical Skills									
Domain	Jobs	Active Learning	Active Listening	Learning Strategies	Critical Thinking	Writing	Speaking	Monitoring	Science	Reading Comprehension	Mathematics	Complex Problem Solving	Programming	Management of Personnel	Management of Material	Management of Financial	Time Management	Negotiation	Social Perceptiveness	Service Orientation	Persuasion	Coordination	Instructing	Systems Analysis	Systems Evaluation	Judgment and Decision	Technology Design	Repairing	Operations Analysis	Installation	Troubleshooting	Equipment Selection	Equipment Maintenance	Quality Control Analysis	Operation and Control	Operations Monitoring
Waterborne	Captains, Mates, and Pilots of Water Vessels	48	48	43	46	45	48	48	21	45	34	45	16	52	41	34	52	37	43	41	39	54	43	43	37	50	23	43	16	NR	39	37	46	43	57	52
	Motorboat Operators	39	41	36	48	39	41	48	7	43	30	43	NR	39	20	14	43	34	43	43	34	48	41	32	32	45	14	41	11	NR	41	37	43	41	57	52
	Shipping, Receiving, and Inventory Clerks	30	43	32	43	39	43	43	NR	45	32	32	9	30	16	16	34	30	36	32	30	41	32	32	23	39	13	NR	9	NR	18	NR	NR	29	29	30
Transveral	Cargo and Freight Agents	39	43	27	52	43	43	45	NR	45	36	41	5	32	20	5	43	45	43	43	41	43	36	30	30	39	5	7	20	NR	20	11	9	29	18	23
	Crane and Tower Operators	34	43	32	43	34	41	43	NR	43	30	32	NR	32	9	9	41	29	29	29	29	43	32	16	29	37	5	39	16	13	43	29	41	41	50	46
	Gas Compressor and Gas Pumping Station Operators	34	43	34	43	41	43	43	18	45	30	43	7	30	18	11	39	30	34	30	30	41	32	34	30	39	16	43	NR	NR	45	30	45	43	54	55
	Gas Plant Operators	43	43	37	46	43	43	50	25	45	41	43	11	41	18	16	43	36	43	30	37	45	39	39	36	43	13	41	16	NR	45	34	43	50	54	63
	Hoist and Winch Operators	30	34	36	37	32	32	37	NR	34	27	34	NR	36	16	16	39	30	32	32	32	48	36	25	23	36	NR	39	NA	NR	34	36	36	36	41	43
	Laborers and Freight, Stock, and Material Movers, Hand	29	30	29	29	30	29	30	NR	30	25	29	NR	27	13	NR	30	25	29	29	27	39	27	25	21	29	NR	18	NR	NR	29	16	21	29	36	36
	Logisticians	50	59	50	59	54	57	66	13	59	48	55	25	54	37	32	54	50	52	48	52	61	43	55	55	57	11	NR	57	NR	NR	NR	NR	32	NR	23
	Logistics Analysts	54	57	43	59	57	48	57	11	57	54	57	25	41	32	36	48	41	43	41	41	45	41	57	55	57	25	NR	37	NR	7	NR	NR	32	NR	29
	Logistics Engineers	55	59	50	61	59	57	55	41	63	57	57	32	52	41	41	55	41	50	43	45	52	43	61	59	57	32	11	54	NR	30	NA	11	41	11	37
	Occupational Health and Safety Technicians	45	57	43	57	55	54	54	37	55	39	46	14	30	25	20	43	43	45	43	45	43	43	43	43	46	14	NR	36	NR	23	NR	NR	41	32	43
	Petroleum Pump System Operators, Refinery Operators, and Gaugers	43	43	41	50	43	43	50	25	48	39	43	14	36	21	21	43	36	41	30	34	43	41	39	37	43	7	37	21	NR	41	27	41	48	55	66
	Pump Operators, Except Wellhead Pumpers	41	43	32	45	39	41	48	20	43	37	41	11	32	25	16	41	30	32	30	30	43	37	30	30	43	13	39	14	NR	41	30	39	39	46	54
	Sailors and Marine Oilers	41	43	37	43	41	43	45	14	45	30	41	NR	39	21	16	43	36	41	41	37	43	43	32	32	43	20	45	NR	NR	45	36	43	45	50	54
	Ship Engineers	45	50	41	55	43	43	54	29	48	34	48	9	45	25	11	43	29	43	39	29	43	41	45	39	45	9	55	18	41	55	43	54	45	55	55
	Supply Chain Managers	54	57	46	57	57	57	59	NR	57	43	57	13	55	54	43	57	54	55	45	52	57	46	54	55	57	20	NR	34	NR	13	NR	NR	23	NR	27
	Tank Car, Truck, and Ship Loaders	39	43	34	41	39	41	45	11	45	30	41	5	39	27	16	41	30	30	30	30	41	37	37	30	41	11	32	NR	NR	36	34	29	41	46	48
	Weighers, Measurers, Checkers, and Samplers, Recordkeeping	39	43	36	43	43	43	45	11	43	39	39	16	39	14	16	41	30	41	43	32	43	34	30	30	41	7	18	NR	NR	20	18	18	39	25	32

Annex C.6. Relative level and risk of automation of abilities in waterborne and transversal transport-related occupations

Ability — Cognitive abilities

Domain	Jobs	Originality	Written Comprehension	Problem Sensitivity	Mathematical Reasoning	Written Expression	Inductive Reasoning	Oral Expression	Visualization	Fluency of Ideas	Oral Comprehension	Speed of Closure	Deductive Reasoning	Category Flexibility	Time Sharing	Flexibility of Closure	Perceptual Speed	Spatial Orientation	Information Ordering	Selective Attention	Memorization	Number Facility
Waterborne	Captains, Mates, and Pilots of Water Vessels	37	50	52	36	50	48	55	46	39	55	45	50	45	46	48	50	63	54	52	43	39
Waterborne	Motorboat Operators	36	41	50	27	39	43	52	50	32	50	36	43	41	46	48	50	55	45	52	37	27
Waterborne	Shipping, Receiving, and Inventory Clerks	30	43	43	30	37	41	45	37	30	45	30	41	43	32	34	41	20	43	34	30	34
Transveral	Cargo and Freight Agents	32	54	43	36	45	43	57	29	36	57	29	43	45	39	34	39	11	43	43	30	37
Transveral	Crane and Tower Operators	30	41	41	30	34	36	45	45	30	50	30	43	36	36	37	45	39	39	45	29	30
Transveral	Gas Compressor and Gas Pumping Station Operators	30	41	46	30	41	45	43	39	32	45	39	46	43	39	43	50	27	43	43	30	30
Transveral	Gas Plant Operators	39	50	54	34	43	46	52	45	36	54	39	50	41	41	54	55	27	46	48	32	39
Transveral	Hoist and Winch Operators	30	36	41	21	30	38	41	41	30	52	29	34	38	38	36	48	25	41	39	32	29
Transveral	Laborers and Freight, Stock, and Material Movers, Hand	29	41	41	20	29	39	41	41	29	43	29	41	39	34	30	30	27	41	41	20	27
Transveral	Logisticians	55	57	59	48	55	57	59	45	54	63	39	66	50	32	43	39	NR	55	37	41	50
Transveral	Logistics Analysts	54	57	55	55	57	57	57	41	54	57	41	57	54	34	48	43	NR	57	46	39	55
Transveral	Logistics Engineers	57	61	61	55	57	59	59	52	57	63	39	61	55	41	46	43	NR	57	45	39	55
Transveral	Occupational Health and Safety Technicians	43	57	59	39	54	57	57	32	43	57	43	57	46	37	48	43	20	46	43	32	37
Transveral	Petroleum Pump System Operators, Refinery Operators, and Gaugers	34	48	52	41	43	50	52	43	36	54	41	54	45	43	54	57	27	54	52	36	39
Transveral	Pump Operators, Except Wellhead Pumpers	29	43	46	39	41	43	46	46	30	52	39	43	45	39	43	54	30	45	46	30	39
Transveral	Sailors and Marine Oilers	32	45	50	30	41	43	46	46	32	55	36	43	43	45	55	46	41	45	45	30	30
Transveral	Ship Engineers	43	57	59	34	50	54	57	52	43	59	41	57	45	43	45	45	32	52	52	34	37
Transveral	Supply Chain Managers	46	61	57	50	57	55	59	41	46	59	36	55	54	41	43	41	NR	54	43	32	45
Transveral	Tank Car, Truck, and Ship Loaders	30	43	43	30	39	41	46	43	30	48	29	41	41	41	43	45	29	41	43	29	30
Transveral	Weighers, Measurers, Checkers, and Samplers, Recordkeeping	30	43	41	37	43	43	45	36	30	50	32	45	46	32	45	45	13	43	45	32	39

Ability — Physical abilities, Psychomotor abilities, Sensory abilities

Domain	Jobs	Gross Body Equilibrium	Gross Body Coordination	Trunk Strength	Dynamic Flexibility	Extent Flexibility	Explosive Strength	Stamina	Dynamic Strength	Static Strength	Rate Control	Finger Dexterity	Manual Dexterity	Multilimb Coordination	Response Orientation	Arm-Hand Steadiness	Speed of Limb Movement	Control Precision	Reaction Time	Wrist-Finger Speed	Glare Sensitivity	Speech Recognition	Auditory Attention	Night Vision	Speech Clarity	Depth Perception	Far Vision	Peripheral Vision	Hearing Sensitivity	Sound Localization	Visual Color Discrimination	Near Vision
Waterborne	Captains, Mates, and Pilots of Water Vessels	39	34	46	14	41	34	30	39	39	45	45	45	46	41	46	14	46	52	29	54	52	46	41	50	50	59	39	45	37	43	52
Waterborne	Motorboat Operators	36	29	43	NR	41	13	23	34	45	45	45	45	45	50	43	27	57	48	30	52	43	48	39	43	45	66	41	41	36	43	46
Waterborne	Shipping, Receiving, and Inventory Clerks	21	27	41	NR	41	16	30	25	41	27	34	41	34	25	36	18	34	27	27	14	41	30	14	43	30	41	23	27	14	34	46
Transveral	Cargo and Freight Agents	7	9	16	NR	16	14	11	13	14	11	30	20	16	13	18	NR	18	14	11	9	43	30	9	43	18	39	11	25	9	29	45
Transveral	Crane and Tower Operators	30	29	37	NR	37	NR	25	29	41	54	43	45	57	50	45	32	59	55	36	43	37	41	27	43	59	59	39	41	29	43	52
Transveral	Gas Compressor and Gas Pumping Station Operators	29	29	41	NR	32	16	27	27	34	45	45	45	45	41	45	23	45	46	29	29	39	43	18	41	37	45	20	39	21	34	46
Transveral	Gas Plant Operators	29	29	36	NR	37	11	27	27	30	39	43	41	43	41	43	18	50	54	30	30	43	54	21	43	36	48	25	43	25	43	48
Transveral	Hoist and Winch Operators	36	29	38	NR	50	NR	27	NA	45	38	39	39	52	46	38	34	55	50	29	34	36	NA	23	34	50	39	29	41	30	34	39
Transveral	Laborers and Freight, Stock, and Material Movers, Hand	23	32	54	16	54	23	45	43	57	34	41	43	52	36	43	25	45	41	16	18	37	29	18	30	37	43	27	29	18	34	45
Transveral	Logisticians	NR	NR	16	NR	NR	NR	NR	7	NR	NR	27	NR	NR	NR	NR	NR	NR	NR	7	NR	55	27	NR	55	5	46	NR	21	NR	25	55
Transveral	Logistics Analysts	NR	NR	9	NR	NR	NR	NR	NR	NR	NR	23	9	NR	NR	9	NR	11	NR	NR	NR	50	30	NR	46	13	39	NR	23	NR	29	55
Transveral	Logistics Engineers	NR	NR	11	NR	NR	NR	NR	NR	NR	NR	27	11	NR	NR	NA	NR	NR	NR	NR	NR	55	30	NR	57	27	43	NR	30	NR	36	57
Transveral	Occupational Health and Safety Technicians	25	23	32	NR	27	14	20	14	18	13	34	20	27	14	25	NR	20	25	16	18	43	29	9	50	29	46	11	30	14	41	55
Transveral	Petroleum Pump System Operators, Refinery Operators, and Gaugers	39	34	39	NR	43	14	29	30	37	41	41	43	41	37	43	23	43	52	34	30	43	50	16	43	34	48	23	43	27	43	50
Transveral	Pump Operators, Except Wellhead Pumpers	30	30	41	NR	45	11	32	32	43	41	45	45	45	39	45	27	46	45	30	29	41	50	18	41	43	45	27	43	18	46	48
Transveral	Sailors and Marine Oilers	45	43	50	NR	48	20	41	41	52	43	45	45	54	41	45	32	54	46	37	50	43	55	36	43	55	63	36	48	41	48	54
Transveral	Ship Engineers	29	30	43	7	48	20	34	30	43	43	46	43	45	43	45	7	55	45	34	27	45	46	18	46	32	43	21	48	32	46	54
Transveral	Supply Chain Managers	NR	NR	11	NR	NR	NR	NR	NR	NR	NR	20	NR	NR	NR	NR	NR	NR	NR	NR	NR	48	25	NR	46	20	43	NR	27	NR	30	50
Transveral	Tank Car, Truck, and Ship Loaders	43	41	52	7	54	16	41	39	55	45	45	45	55	39	45	32	57	54	29	39	39	43	29	41	52	45	30	43	29	41	46
Transveral	Weighers, Measurers, Checkers, and Samplers, Recordkeeping	23	27	30	NR	34	14	29	27	29	16	41	34	34	13	37	18	36	34	11	11	45	39	11	43	20	43	13	30	13	36	57

Skills Move Us Forward: Transport Workforce Skills in the Age of AI
Summary and Conclusions

The growing role of artificial intelligence in the transport sector drives demand for new skills while placing pressure on roles that rely on automatable tasks. Workers face mounting expectations to reskill and adapt to a more automated labour market in order to harness AI's benefits. At the same time, overreliance on AI raises concerns about skill erosion and related risks. Identifying and retaining critical expertise is therefore essential to improving safety and the operational resilience of transport systems.

The report calls for a proportionate, anticipatory approach to skills development and AI governance, with an emphasis on retaining critical expertise and building the enabling skills that underpin it. Drawing on five guiding principles, it outlines how public authorities can reduce barriers to reskilling, by addressing motivation, capability and access to training, to support the safe, responsible and resilient adoption of AI in transport.

International Transport Forum
2 rue André Pascal
F-75775 Paris Cedex 16
+33 (0)1 73 31 25 00
contact@itf-oecd.org
www.itf-oecd.org

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