SUPPLY CHAIN MANAGEMENT

The Role of Automation and Digital Technologies in Improving Australian Freight Efficiency

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Abstract

Australia moves large volumes of bulk commodities, containers and consumer goods over long distances with a road-dominated freight system, so small gains in cost, time and energy per tonne carried translate into large national benefits. The question addressed here is whether, and under what conditions, automated and digitally enabled operations make Australian freight more efficient. Thirty refereed journal articles, each with a final publication year in the 2020–2025 window, form the evidence base; they were chosen by systematic integrative review and organised around a review of road freight and alternative modes in Australia and a study of artificial intelligence use cases in freight logistics. Seven of the articles examine Australian freight directly, and the others provide technical and international evidence on road, rail, terminal and last-mile operations. Each study was coded by technology family and by the efficiency dimension it addresses. The evidence indicates that automated and platooned trucks lower operating cost and energy use in modelled scenarios, that driverless heavy-haul rail and digitally monitored wagons support higher asset productivity, and that telematics, platforms and analytics improve coordination and visibility. Container terminal automation shows mixed productivity results, and digitalisation can reduce efficiency before it improves it. Gains depend on interoperability, investment cost, workforce acceptance and skills, and regulation, while Australian logistics providers report integration difficulties and partner costs as major barriers. A conceptual model is proposed that links technology layers to efficiency mechanisms and outcomes under these moderating conditions, together with propositions and implications for freight policy and practice in Australia.

1 Introduction

Freight is the circulatory system of the Australian economy. Iron ore, coal and grain travel from inland mines and farms to export ports, containers move between ports and distribution centres in the capital cities, and parcels flow to households spread across a continent. Demand for freight has grown with domestic consumption and international trade, and most of it is carried by trucks, which bring congestion, greenhouse gas emissions and risks to public health and safety (Peters et al., 2023). Because distances are long and population density outside the cities is low, the cost, time and energy required to move each tonne have an unusually large bearing on national productivity.

Two broad avenues are open for improving that efficiency. The first is automation, which substitutes machines for human operation in driving, handling and delivery: automated trucks and platoons, driverless trains, automated container terminals, drones and delivery robots. The second is digitalisation, in which sensors, connectivity, data platforms and analytical tools change how freight is planned, monitored and coordinated. The two are linked, since automated equipment depends on data, and the value of data is often realised through automated decisions. Industry interest in both is high, yet the evidence that they improve efficiency in practice is uneven. Studies of automated container terminals, for example, find no strong evidence that automation raises handling productivity (Majoral

et al., 2024), and an analysis of truck drivers in retail logistics found that a shift in digitalisation first reduced efficiency before the loss was recovered and surpassed (Loske and Klumpp, 2022).

The Australian setting adds specific conditions. The logistics industry has been slower than other sectors to adopt blockchain (Chen et al., 2024), logistics service providers face pressure to deploy emerging technologies while contending with operational challenges heightened by the pandemic (Nand et al., 2023), and heavy-haul rail operators must decarbonise locomotives that run long routes with heavy loads (Knibbe et al., 2022). Meanwhile, the policy instruments that shape modal choice, such as fuel tax credits, have yet to be fully evaluated (Peters et al., 2023).

Existing reviews tend to concentrate on a single technology, such as platooning (Zhang et al., 2020), the Internet of Things (Song et al., 2021) or artificial intelligence (Chen et al., 2024), or on a single mode. Few bring automation and digital technologies together across modes and relate them to the efficiency problems of a specific national freight system. This paper addresses that gap for Australia. It reviews 30 studies, maps them against technology families and dimensions of efficiency, sets out the conditions under which gains appear, and proposes a conceptual model with testable propositions.

2 Aim and research questions

The aim of this paper is to explain how automation and digital technologies can improve the efficiency of Australian freight operations, and to identify the conditions that govern whether expected gains are realised. The work pursues four objectives: (1) to describe the efficiency challenges of the Australian freight system that technology might address; (2) to assess the evidence on how automation in road, rail, terminal and last-mile operations affects cost, time, energy use and productivity; (3) to examine how sensing, platforms, analytics and distributed ledgers improve the coordination and visibility of freight flows; and (4) to develop a conceptual model that connects technologies, efficiency mechanisms, outcomes and moderating conditions.

Three research questions guide the review. RQ1: Which automation and digital technologies have demonstrated or modelled efficiency effects in freight operations, and on which dimensions of efficiency? RQ2: What organisational, technical, workforce and regulatory conditions moderate these effects, particularly for Australian operators? RQ3: How should Australian freight policy and practice prioritise technologies to obtain efficiency gains across modes?

3 Review method

A systematic integrative design was chosen because the relevant evidence spans engineering models, cost and scenario analyses, surveys, interviews, case studies and literature reviews, and these cannot be pooled statistically. Integration allows such heterogeneous findings to be compared and combined into a conceptual account, provided that each step of selection is explicit, and each claim can be traced to a source.

Records were retrieved in November 2026 from an open bibliographic index, and the metadata of every candidate was confirmed against its registration record. Search strings joined technology terms (automation, autonomous truck, platooning, driverless train, automated container terminal, drone delivery, Internet of Things, telematics, digital platform, artificial intelligence, blockchain, digitalisation) with freight terms (freight, road freight, rail freight, logistics, last mile, container

terminal) and, in a second pass, with Australia and Australian. Titles and abstracts were screened first, and full records were then assessed against the inclusion rules.

To be included, an article had to be a refereed journal publication in English with a final publication year between 2020 and 2025, and it had to report evidence, models or structured analysis on how a technology affects freight or logistics operations, or on the efficiency conditions of the Australian freight system. Reviews were retained where they consolidated a technology-specific literature. Items without an abstract, conference papers, commentaries and studies concerned with passenger transport alone were excluded. When several candidates covered the same technology and mode, priority went to Australian studies and to those reporting quantified effects.

The two anchor articles were the literature study of road freight transport and alternative modes in Australia by Peters et al. (2023) and the analysis of artificial intelligence use cases in freight logistics by du Plessis et al. (2025). The final set of 30 articles comprises five on automated and platooned road vehicles, three on rail automation and digital wagons, four on container terminal automation, two on last-mile automation, five on sensing and telematics, two on digital freight platforms, four on artificial intelligence, analytics and digitalisation, two on adoption barriers in Australian logistics, and three on the modal and pricing context of freight. Seven articles have an Australian setting.

For each article the setting, mode, technology, method and reported effects were extracted. Each study was then coded against five efficiency dimensions: operating cost; time and throughput; energy and emissions; visibility and coordination; and labour and skills. A study could be coded to more than one dimension, and the codes underlie Figure 1. Findings were compared within and across technology families, and divergent results were examined for differences in setting or method. Non-Australian evidence is reported as such, and modelled or simulated effects are distinguished from observed ones. All findings are drawn from the published studies, and the conceptual model is offered for future testing.

4 The efficiency problem in Australian freight

Several features of the Australian freight system define the problems that technology is expected to solve. Peters et al. (2023) reviewed evidence on road freight and its alternatives and observed that growing freight volumes increase greenhouse gas emissions, with consequences for climate, air pollution, public health and safety. They compared Australia with the European Union, where the Marco Polo programme aimed to shift transit traffic off roads and onto shipping, rail and inland waterways, and noted that Australia's Fuel Tax Credit was introduced partly to address similar issues, arguing that the impact of such schemes now needs to be analysed. Their review found that alternative modes reduce carbon dioxide over long distances and that renewable fuels such as electricity and hydrogen may be used in trucks, although research on renewable fuels was limited.

Modal shift is hampered by barriers that technology can only partly remove. Karam et al. (2023) reviewed 104 studies and identified 31 barriers to multimodal freight transport, grouped into terminal, network, management, regulation and subsidies, delivery characteristics and interoperability. Their framework shows that many barriers sit at the interfaces between modes, which is precisely where digital coordination might help. Bossong et al. (2025) made a similar observation for intermodal transport, which combines the environmental advantages of rail with the flexibility of road but adds interfaces that reduce efficiency and call for automation through digital platforms.

Urban freight raises a different set of problems. Hensher et al. (2023) developed an aggregate freight demand model for the Greater Sydney Metropolitan Area and integrated it with a passenger model to test distance-based charges for trucks and cars, showing that road pricing reforms aimed at passengers also affect the movement of freight vehicles and should not ignore truck traffic. Network congestion can be diagnosed with new data sources: using telematics big data, Ma et al. (2024) defined freight bottlenecks at the network level and built a scalable method to detect and rank them, arguing that precise detection supports goods movement strategies, policy and supply chain efficiency. Table 1 summarises the technology families in the corpus and the efficiency effects that the studies report.

Table 1. Technology families in the corpus and the efficiency effects reported.

Technology family	Mode or setting	Reported efficiency effect	Key sources
Automated and platooned trucks	Road freight; South Korea, United Kingdom, simulation	Lower total cost of operation; profitable electric trucks over longer ranges; fuel savings from reduced drag	Lee et al. (2023); Ghandriz et al. (2020); Zhang et al. (2020); Paddeu and Denby (2022); Kim et al. (2022)
Rail automation and digital wagons	Heavy-haul and freight rail; Australia, Sweden	Automation taxonomy for open networks; fault detection; route-specific battery or hydrogen solutions	Ramirez et al. (2022); Moya et al. (2023); Knibbe et al. (2022)
Container terminal automation	Ports; international	Higher-quality work and profit, but no strong evidence of higher productivity	Yu et al. (2022); Wai Kok et al. (2024); Majoral et al. (2024); Notteboom et al. (2025)
Drones and delivery robots	Last mile; urban and rural	Lower cost and faster delivery than trucks; lower emissions than diesel trucks in rural areas	Boysen et al. (2021); Raghunatha et al. (2023)
Sensing and telematics	Road, rail and maritime freight	Holistic efficiency measurement; shared analytics and risk services	Song et al. (2021); Miler et al. (2020); Heinbach, Meier, et al. (2022); Rajak et al. (2024); Ma et al. (2024)
Digital freight platforms	Road and intermodal freight	Visibility, optimisation and analytics services; adoption contested	Heinbach, Beinke, et al. (2022); Bossong et al. (2025)
Artificial intelligence and analytics	Logistics operations	77 use cases; optimised routes and resources; dip-then-rise efficiency	du Plessis et al. (2025); Chen, Men, et al. (2024); Feng and Ye (2021); Loske and Klumpp (2022)
Blockchain and emerging technologies	Australian logistics	Adoption limited by investment cost and partner integration	Chen, Vandchali, et al. (2024); Nand et al. (2023)

5 Automation across freight modes

Automation in freight extends across four operating environments: the highway, the railway, the container terminal and the final delivery to customers. The evidence for each differs in maturity and in the extent to which effects have been observed rather than modelled.

5.1 Automated and platooned road freight

Road freight is widely regarded as a likely first mover in autonomous technology because of the potential to reduce costs for logistics companies (Paddeu and Denby, 2022). The strongest quantified evidence concerns operating cost. Lee et al. (2023) combined cost–benefit analysis and scenario planning for a South Korean middle-mile corridor linking a port with a distribution centre, using data from a freight operator involved in an autonomous truck pilot. In their base scenario, the monthly total cost of operation fell by between about 42% and 56% depending on truck size, with lower driver wages a substantial component, although remote operation emerged as a new cost. Even the most pessimistic scenario showed savings for every truck size examined.

Automation also interacts with electrification. Ghandriz et al. (2020) minimised the total cost of ownership across 3,072 transport scenarios and found that automated driving made battery electric heavy vehicles profitable over travel ranges four times longer than those achievable with a human driver, with up to 20% lower cost of ownership when propulsion and charging infrastructure were optimised together. The finding is potentially relevant to Australia's long interstate corridors, although it has not been tested there.

Platooning, in which trucks travel in tandem at small gaps, targets energy efficiency. Zhang et al. (2020) reviewed studies showing that reduced aerodynamic drag can significantly improve fuel economy, and examined the coordination methods and speed control strategies needed to raise the share of travel in platoons. Paddeu and Denby (2022) co-designed a platooning roadmap to 2050 with freight stakeholders in the United Kingdom and found that adoption was highly uncertain; benefits would come first from a small pool of trucks with low automation and later from a larger pool with high automation. Kim et al. (2022) argued that expanding the workforce alone cannot solve the problems of the truck logistics market and proposed platooning as a more efficient path to adopting autonomous trucks, while acknowledging that the technology brings problems as well as benefits.

5.2 Rail Automation and digital wagons

Rail has particular significance for Australia because heavy-haul lines carry bulk exports over long distances. Ramirez et al. (2022) reviewed automation taxonomies for freight rail after the announcement of the first fully automated heavy-duty, long-haul commercial freight operation. They explained why automation has been slower in freight than in urban metros, which have run without drivers for more than 50 years: freight trains operate on open rail networks, whereas metros operate on closed ones, yet the same taxonomies are often applied to both, which obscures the tasks that can realistically be automated in freight.

Digital monitoring of rolling stock offers a complementary path. Moya et al. (2023) installed sensors for train composition, integrity, asset condition and continuous positioning on freight wagons operating on a commercial line in Sweden, and field tests demonstrated the detection of faults and anomalies, laying the ground for real-time analysis and proactive maintenance. Energy efficiency is a third strand. Using data from locomotives in Australian rail freight, Knibbe et al. (2022) showed that batteries alone cannot meet the energy needs of every heavy haul; they identified lithium iron phosphate as the most suitable current chemistry and concluded that battery-only systems give the lowest cost for low-energy hauls, while high-energy hauls need a battery and hydrogen combination.

5.3 Container terminal Automation

Container terminals were among the first freight settings to automate at scale, and the evidence there is the most mixed. Yu et al. (2022) analysed more than 600 papers on yard management in automated terminals and argued that yard operations are the key to container handling efficiency. Ten experts consulted by Wai Kok et al. (2024) indicated that automated terminals produced higher-quality work and higher terminal profits, but needed highly skilled workers who could adapt theory to practice, solve problems and work with automated equipment.

Productivity outcomes are less clear. Majoral et al. (2024) combined academic and industry sources and concluded that automation had not been shown convincingly to raise productivity, although it might lower costs for operators; in many cases productivity was worse, and semi-automated terminals were still preferred because of better handling times. Stakeholder relations shape the outcome as well. Surveying operators of automated terminals, Notteboom et al. (2025) found that port authorities, ocean carriers and governments were seen as the main supporters, whereas dockworkers expressed the greatest opposition, especially in Europe and the United States, where unions are strong. For Australian terminals, these findings imply that automation decisions involve labour relations and process redesign as much as equipment.

5.4 Last-Mile Automation

The last mile is a costly and congested segment of urban freight. Boysen et al. (2021) surveyed established and novel delivery concepts, including drones and autonomous delivery robots, and set out the operational research problems that must be solved to plan and run each concept. Raghunatha et al. (2023) assessed large electric drones against diesel and electric trucks and found that drones had lower emissions than diesel trucks in rural deliveries, did not outperform electric trucks on emissions because of the energy needed for take-off and landing, and were cheaper and faster than road vehicles because of their high degree of automation. Their results for rural deliveries and emergency uses are pertinent to Australia's dispersed communities, though the authors also identify open questions about drone size and landing practices.

6 Digital technologies and freight information flows

Whereas automation changes how vehicles and equipment operate, digital technologies change what operators know and how they coordinate. Four groups of technologies are represented in the corpus: sensing and telematics, digital freight platforms, artificial intelligence and analytics, and distributed ledgers.

6.1 Sensing, telematics and the Internet of Things

The Internet of Things generates large volumes of data on vehicles, loads and facilities, and Song et al. (2021) reviewed its applications across transport, warehousing, loading and unloading, distribution and information processing, arguing that it can help an industry that still faces high costs and low efficiency. Measuring these benefits is not straightforward. Miler et al. (2020) noted that previous research had evaluated individual modules rather than whole telematics systems, and developed a matrix tool that they verified as a reliable means of comparing the holistic efficiency of telematics in the operational management of road transport enterprises.

Telematics can also be shared among stakeholders. Through design science research, interviews with transport stakeholders and a prototype, Heinbach, Meier, et al. (2022) designed a shared freight

service intelligence platform built on mobile telematics, supporting transport, fleet and risk management through analytics, anomaly detection, risk prediction and data exchange. Adoption drivers vary across modes. Rajak et al. (2024) weighted adoption drivers for road, rail and maritime freight and found competitive advantage, management support and security and privacy most important overall, investment cost most important for road, management support for rail and ease of use for maritime transport.

6.2 Digital freight platforms

Platforms match shippers with carriers and offer data-driven services. Heinbach, Beinke, et al. (2022) developed a typology of digital platforms for road freight transport management, identifying eight platform types across 14 dimensions and services centred on visibility, optimisation and analytics. Platforms can also support intermodal transport, but their adoption is contested. In a multiple-case study, Bossong et al. (2025) identified 30 adoption factors and found that sellers of intermodal services feared greater market transparency and interface standardisation, whereas buyers favoured both, and they proposed nine levers to raise adoption and thereby supply chain automation. For a fragmented Australian road freight industry with many small carriers, the same tension between transparency and competitive position is likely to influence uptake.

6.3 Artificial intelligence, analytics and smart logistics

Artificial intelligence extends the use of freight data from monitoring to decision-making. Through a literature review, expert interviews, facility visits and generative tools, du Plessis et al. (2025) identified 77 distinct use cases across holistic supply chain opportunities, transport vehicles and logistics facilities, and found that the refereed literature had not previously set out such use cases comprehensively. Chen, Men, et al. (2024) reviewed artificial intelligence models for logistics optimisation, including machine learning, generative models and metaheuristics combined with simulation, and showed how they can improve resource use, route planning and emissions performance. Feng and Ye (2021) reviewed operations management research on smart logistics, which they describe as a response to the growing complexity and volume of logistics operations enabled by the Internet of Things, communication technologies and artificial intelligence.

Evidence on realised efficiency comes with an important caution. Using data envelopment analysis of truck drivers and a productivity index over time et al. (2022) showed that moving to a new level of digitalisation initially lowers efficiency, but the loss can be compensated and even surpassed later, with positive long-term effects from several successive digitalisation steps. The implication is that early efficiency measurements may understate the eventual return on digital investment, and that operators need to budget for a learning period.

6.4 Adoption in Australian logistics

Australian studies show where adoption stalls. Applying fuzzy decision analysis within a technology, organisation and environment framework, Chen, Vandchali, et al. (2024) identified 13 barriers to blockchain adoption in Australian logistics and found that the cost of investment and difficulties of integration among partners were the most prominent, especially within organisations. Interviews and a focus group with Australian industry stakeholders, reported by Nand et al. (2023), identified internal organisational factors that drive optimisation of supply chain networks as drivers of technology deployment, while the pandemic acted as an external driver; the study also recorded the

barriers and actions that logistics service providers considered for sustainable operations after the pandemic.

7 Evidence synthesis: conditions for efficiency gains

Table 2 summarises the conditions under which the reviewed studies report or anticipate efficiency gains, grouped by the level at which they operate.

Table 2. Conditions that moderate efficiency gains from freight technologies.

Condition	Evidence from the corpus	Level	Key sources
Complementary investment	Gains depend on joint optimisation of vehicles, energy systems, yards and processes	Firm and network	Ghandriz et al. (2020); Yu et al. (2022)
Interoperability and standards	Barriers concentrate at modal and organisational interfaces	Network and sector	Karam et al. (2023); Bossong et al. (2025)
Investment cost and scale	Cost of investment and partner integration lead Australian barriers; road operators weigh cost most	Firm	Chen, Vandchali, et al. (2024); Rajak et al. (2024)
Learning and time	Efficiency falls after digitalisation before recovering; automation benefits arrive in phases	Firm	Loske and Klumpp (2022); Paddeu and Denby (2022)
Workforce and stakeholders	New skills required; wage savings offset by remote operation; dockworker opposition	Firm and sector	Wai Kok et al. (2024); Lee et al. (2023); Notteboom et al. (2025)
Policy and infrastructure	Impact of fuel tax credits still to be analysed; pricing reform must include trucks	National and urban	Peters et al. (2023); Hensher et al. (2023)

Figure 1 shows how the 30 studies are distributed across technology families and efficiency dimensions. Three patterns are evident. First, automation studies concentrate on operating cost, energy and labour, whereas digital technology studies concentrate on visibility and coordination. Second, time and throughput are addressed by studies across most families, but the strongest throughput evidence, from container terminals, is also the most contested. Third, energy and emissions are addressed by almost every family, most frequently in the road vehicle studies, which suggests that efficiency and decarbonisation are increasingly evaluated together.

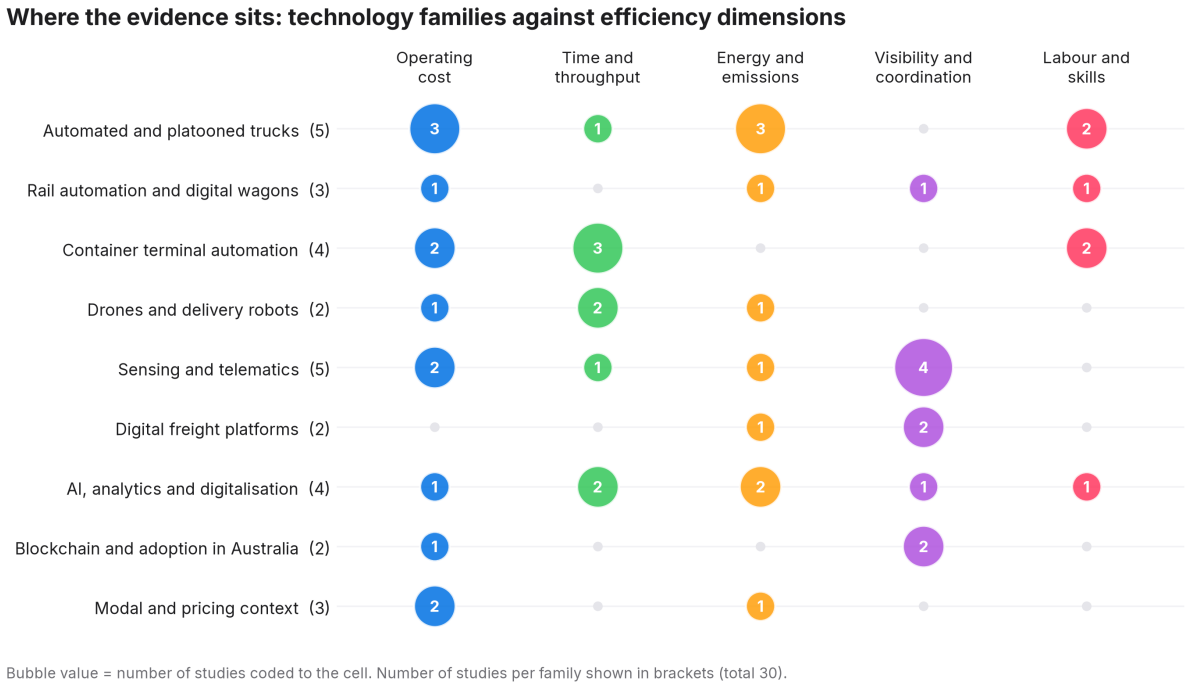


Figure 1. Coverage of efficiency dimensions by technology family across the 30 reviewed studies (author's coding; a study may address several dimensions).

Several cross-cutting conditions emerge. The first is that many effects are modelled rather than observed. The cost savings from autonomous trucks (Lee et al., 2023), the profitability of automated electric trucks (Ghandriz et al., 2020) and the advantages of drones (Raghunatha et al., 2023) come from scenario and systems analyses, while observed evidence from terminals is less favourable (Majoral et al., 2024). The second is that efficiency gains depend on complementary change. Battery electric trucks became profitable when automation, propulsion and infrastructure were optimised jointly (Ghandriz et al., 2020), and terminal automation depends on yard management (Yu et al., 2022) and skilled workers (Wai Kok et al., 2024).

The third condition is interoperability. Barriers to multimodal transport lie largely at interfaces (Karam et al., 2023), platforms create value through standardisation that some participants resist (Bossong et al., 2025), and integration difficulty among partners is a leading barrier in Australia (Chen et al., 2024). The fourth concerns time: digitalisation can depress efficiency before it raises it (Loske and Klumpp, 2022), and platooning benefits would grow in phases as automation levels rise (Paddeu and Denby, 2022). The fifth is the workforce. Automation alters the skills required (Wai Kok et al., 2024), changes the cost structure through lower wages and new remote-operation costs (Lee et al., 2023), and encounters the strongest opposition from dockworkers (Notteboom et al., 2025).

The Australian studies fit these conditions closely. Heavy-haul rail decarbonisation depends on route-specific energy demand (Knibbe et al., 2022), adoption of blockchain is constrained by cost and integration among partners (Chen et al., 2024), and service providers link technology deployment to internal network optimisation goals (Nand et al., 2023). In each case the technology is available, but its efficiency value depends on how well it fits the operating context, the partners involved and the capability of the adopting firm. This observation supports treating context as part of the explanation rather than as a source of noise.

8 Conceptual model and propositions

Figure 2 presents the proposed model. It arranges technologies in four layers: physical automation of vehicles and handling equipment; sensing and connectivity; data platforms and exchange; and analytics and intelligence. These layers act through five efficiency mechanisms: substitution of labour in repetitive operating tasks; better use of vehicles, wagons and terminal equipment; lower energy use per unit carried; tighter coordination across actors and modes; and optimisation of routes, schedules and network flows. The mechanisms produce outcomes measured as cost per unit, transit time and throughput, reliability and emissions. Five conditions moderate the links: interoperability and standards, investment cost and scale, workforce skills and acceptance, regulation and infrastructure, and Australian distances and freight density.

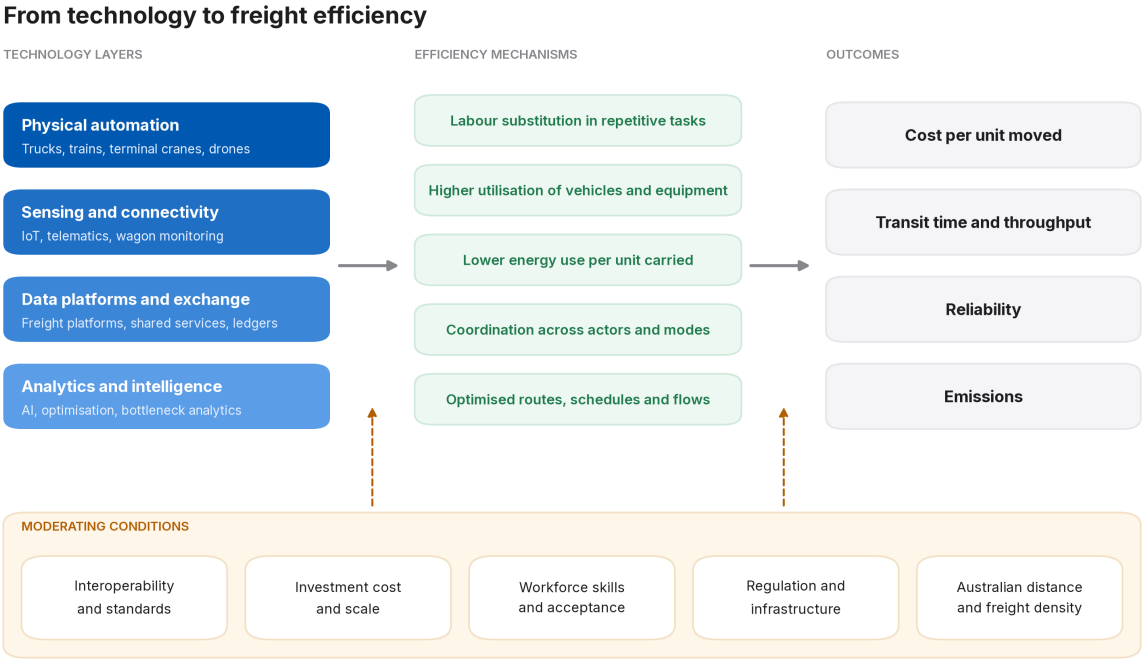


Figure 2. Conceptual model linking freight technology layers to efficiency mechanisms and outcomes under moderating conditions.

Four propositions follow from the synthesis. P1: Efficiency gains from vehicle automation in Australian road freight will be largest on long, repetitive corridors where automation is combined with electrification and charging infrastructure. P2: Digital coordination technologies will raise multimodal and intermodal efficiency only where interfaces between modes and actors are standardised. P3: The efficiency returns on digitalisation in freight firms follow a dip-then-rise pattern, so evaluations conducted soon after adoption will understate long-term returns. P4: Terminal and rail automation will deliver higher productivity where process redesign and workforce development accompany the investment in equipment.

The model differs from technology-specific frameworks in two ways. It treats automation and digitalisation as connected layers, since automated vehicles and equipment depend on the sensing, data and analytics layers to deliver their full benefit. It also treats Australian geography as a moderator rather than a backdrop, recognising that long distances favour some technologies, such as automated

electric trucks and drones for remote delivery, and weaken the case for others that rely on dense networks.

9 Implications for Australian freight policy and practice

For governments, the evidence suggests that infrastructure and regulation determine whether modelled gains are achieved. Charging and refuelling infrastructure on long corridors, rules for automated and platooned trucks, and airspace rules for drones fall within public responsibility. The call to analyse the impact of fuel tax credits (Peters et al., 2023) points to a wider need to assess whether freight policy instruments encourage efficient technologies. Road pricing reform in the cities should incorporate freight explicitly, as Hensher et al. (2023) demonstrated for Sydney, and network-level analysis of telematics data can direct investment to the bottlenecks that impose the greatest delays (Ma et al., 2024).

For industry, the priority is to build the data and interoperability foundations before investing in the most advanced automation. Shared telematics services (Heinbach et al., 2022), platforms with agreed standards (Bossong et al., 2025) and condition monitoring of assets (Moya et al., 2023) can deliver coordination gains with lower capital outlay. Because investment cost and partner integration are leading barriers (Chen et al., 2024), industry associations and consortia may lower the cost of adoption for smaller carriers. Rail operators can use route-level energy models to choose between battery and hybrid hydrogen solutions (Knibbe et al., 2022). Sequencing also matters. Coordination technologies that improve visibility create the data and process discipline on which later automation depends, so an operator that starts with telematics and shared data is better placed to evaluate and adopt automated equipment. Evaluations should be designed with this in mind, measuring efficiency over several years rather than in the first months after adoption (Loske and Klumpp, 2022).

For the workforce, automation implies a shift toward problem-solving, technical and cognitive skills (Wai Kok et al., 2024). Communities view terminal automation more positively when it is presented as a way of addressing the externalities of terminal operations (Notteboom et al., 2025), so early engagement with unions and communities may reduce resistance and improve the design of new operating models. Training programmes that prepare drivers, rail operators and terminal workers for supervisory and remote-operation roles would help retain experience within the industry.

10 Limitations and future research

Several limitations qualify these conclusions. Only seven of the 30 studies have an Australian setting, so much of the technology evidence comes from South Korea, Sweden, the United Kingdom and multinational samples, and transferring it requires care. Many effects are modelled, and the modelling assumptions about wages, energy prices and adoption rates may not hold in Australia. The coding of studies to efficiency dimensions involved judgement, and the counts in Figure 1 describe the attention of the literature rather than the size of effects. The review relied on published abstracts and records, and the period from 2020 to 2025 excludes earlier and later evidence.

Future research could test the propositions with Australian operating data, for example through trials of automated electric trucks on interstate corridors, before-and-after studies of digitalisation in transport firms, and analyses of productivity in Australian terminals. Comparative studies of platform adoption among small carriers, and research on how workforce agreements shape the outcomes of automation, would also add value.

11 Conclusion

This review has examined how automation and digital technologies can improve the efficiency of Australian freight. Across the corpus, vehicle automation lowers cost and energy use on the road in modelled scenarios, rail automation and monitoring support asset productivity, and telematics, platforms and analytics improve coordination. Gains are not automatic: terminal automation has produced mixed productivity, digitalisation can reduce efficiency before raising it, and interoperability, investment cost, workforce skills and regulation condition the outcome. Australian logistics firms identify investment cost and partner integration as leading barriers. The proposed model and propositions offer a basis for prioritising technologies and for testing their effects in the Australian freight system.

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