SciencesPo

AI for Energy Efficiency

Emerging Policy Initiatives and Lessons from Case Studies

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Abstract

This report presents an overview of public policies on AI for energy efficiency across seven international case studies spanning the buildings, transportation, and cross-sectoral energy systems. It proposes an analytical framework to assess each initiative along two dimensions: completeness of its design and implementation, and its potential for replicability across different contexts. It finds that while AI holds significant potential for reducing energy consumption, deployment remains uneven and largely small-scale. Key findings across sectors suggest that digital infrastructure is a prerequisite for AI deployment, that significant challenges related to data collection frameworks and data availability remain, and that further research and innovation is needed to address existing technological gaps. The report also outlines sector-specific implications for policymakers seeking to scale AI-driven energy efficiency initiatives.

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Overview

Energy efficiency has become increasingly urgent as geopolitical tensions strain value chains and climate pressures intensify. Research and pilot cases showed AI offers new tools to optimise consumption, but its substantial resource footprint complicates deployment. Although countries and cities are beginning to use AI in Energy Efficiency (EE) projects, efforts remain small-scale, and public data and evaluations are often incomplete. This report reviews current policy initiatives integrating AI into EE, drawing on international case studies. It develops a benchmark to compare policies and identify enabling factors and constraints for replication. The following sections summarise the literature, present the analytical framework and case examples, and conclude with implications and barriers for future policy making.

Artificial Intelligence

Amid rapid advances in AI, its potential for improving EE has drawn growing attention. Before assessing its potential, it is necessary to clarify the scope.

According to the latest OECD definition "an AI system is a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, 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"[1]. This report focuses on **narrow AI**—systems designed to perform specific tasks within defined domains.[2] Relevant subfields include machine learning, natural language processing, computer vision, optimisation, knowledge-based systems, robotics, and automated planning and scheduling.[3] Our analysis examines public projects using these technologies and improving EE.

AI for Energy Efficiency vs Energy Efficient AI

Based on literature review, a key differentiation emerges when we speak of AI and EE: one addresses the use of energy by AI while the other is about AI to streamline energy use. First, because of the issues related to fossil fuel dependency - from energy security to climate change impacts - increasing attention has been given to ***energy efficient* AI.**

AI technologies are resource-intensive both materially and energetically. Training and operating models often require multiple high-performance GPUs[4]—NVIDIA, for example,

[1] OECD. *Explanatory memorandum on the updated OECD definition of an ai system*. OECD Artificial Intelligence Papers No. 8. 2024.4, https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/03/explanatory-memorandum-on-the-updated-oecd-definition-of-an-ai-system_3c815e51/623da898-en.pdf.

[2] UNESCO and OECD, G7 toolkit for artificial intelligence in the public sector, G7 Presidency Report (n.d.), accessed April 22, 2026, https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/10/g7-toolkit-for-artificial-intelligence-in-the-public-sector_f93fb9fb/421c1244-en.pdf.

[3] Raheemat O. Yussuf and Omar S. Asfour, "Applications of Artificial Intelligence for Energy Efficiency throughout the Building Lifecycle: An Overview," *Energy and Buildings* 305 (February 2024): 113903, https://doi.org/10.1016/j.enbuild.2024.113903.

[4] James O'Donnel and Casey Crownhart, *We Did the Math on AI's Energy Footprint. Here's the Story You Haven't Heard.*, May 20, 2025, https://www.technologyreview.com/2025/05/20/1116327/ai-energy-usage-climate-footprint-big-tech/.

estimates a carbon footprint of 1,312 kg CO_2e for a single unit[5]. AI systems also depend on extensive data collection and storage, which increases reliance on data centres. Cloud-based AI, in particular, raises concerns about rising electricity demand: according to the IEA, data-centre consumption is projected to grow by around 15% per year between 2024 and 2030—over four times faster than electricity demand in all other sectors[6]. Therefore, several scholars have focused on reducing consumption of energy in AI systems, as an enabling objective to achieve EE targets.[7] In some cases, attention has been given on the advantages of edge computing vis-a-vis cloud computing to make AI integrated to Internet of Things devices more energy efficient.[8]

However, in this report, the main focus is on AI for EE, i.e. the benefits of integrating AI technologies to optimize energy use. Because the field is still new, research remains limited and policy initiatives are not yet scaled.

AI for EE: literature & scope

AI for EE is still an emerging field. Most research focuses on AI in energy systems—such as improving renewable generation through better data and system optimisation.[9]—while fewer studies examine AI for end-use EE, meaning the energy consumed directly by final users.[10]

Research on the use of AI for end-use energy efficiency remains limited and largely technical as opposed to policy approaches. Existing research illustrated how AI-enabled energy management in buildings can support grid balancing, and in transportation to improvements in traffic flow, EV charging optimisation, and load shifting through real-time data and machine learning.[11] Although policy-oriented work is scarce, the available evidence indicates significant potential—meriting closer attention from policymakers.

In the next section, we illustrate the analytical framework used to assess the case studies and improve their comparability.

Analytical Framework

As explained in the introduction, our report aims to provide both an overview of the existing policies on AI improving EE but also assess their completeness and replicability. For this reason, we built a scale for each of the two parameters for readers to compare the different initiatives against each other and contextualise the findings with policy constraints. At the

[5] NVIDIA, "Product Carbon Footprint (PCF) Summary for NVIDIA HGX H100," Datasheet, NVIDIA, n.d., https://images.nvidia.com/aem-dam/Solutions/documents/HGX-H100-PCF-Summary.pdf.
[6] IEA, *Energy and AI* (2025), https://www.iea.org/reports/energy-and-ai.
[7] Ignacio Hidalgo et al., "Sustainable Artificial Intelligence Systems: An Energy Efficiency Approach," preprint, December 2, 2023, https://doi.org/10.36227/techrxiv.24610899.v1.
[8] Minseon Kang and Moonju Park, "Power Estimation and Energy Efficiency of AI Accelerators on Embedded Systems," *Energies* 18, no. 14 (2025): 3840, https://doi.org/10.3390/en18143840.
[9] Ahmad Hamdan et al., "AI in Renewable Energy: A Review of Predictive Maintenance and Energy Optimization," *International Journal of Science and Research Archive* 11, no. 1 (2024): 718–29, https://doi.org/10.30574/ijsra.2024.11.1.0112.
[10] European Commission. Eurostat, *Shedding Light on Energy in Europe*, Shedding Light on Energy in Europe (Publications Office, 2025), https://doi.org/10.2785/8045944.
[11] Sreedhar Madichetty et al., "Smart Energy-Efficient Transportation Systems," in *Handbook of Power Electronics in Smart Grids and Intelligent Energy* (Elsevier, 2026), https://doi.org/10.1016/B978-0-323-95045-9.00002-0.

beginning of each case study, the reader will find a visual indicator for the completeness scale and the replicability scale.

Completeness Scale:

This scale provides two types of information: first, how much data is publicly available and second, how complete, and therefore how confident decision-makers can be regarding the results and effectiveness of the project.

Level	Label	Definition	Visual indicator
1	Planned	Policy announced or funded, no deployment yet, no data available	🔵⚪⚪⚪
2	Pilot	Small scale implementation (one city/line/building), fragmented or minimal data available	🔵🔵⚪⚪
3	Operational	Small scale implementation, complete/comprehensive data available, but still expanding and/or waiting to be scaled	🔵🔵🔵⚪
4	Mature	Deployed at scale, multi-year results, independently evaluated	🔵🔵🔵🔵

Replicability scale[12]**:**

Based on the points accumulated across four parameters, the governance, the technical transferability, the economic accessibility and the knowledge requirement, each case study will have a score from 0 to 4.

Score (number of points accumulated)	Level of replicability	Visual indicator
0	Not replicable	⚪⚪⚪⚪
1	Low	🔵⚪⚪⚪
2	Medium-low	🔵🔵⚪⚪
3	Medium-high	🔵🔵🔵⚪
4	High	🔵🔵🔵🔵

[12] Detailed description for the replicability scale can be found in the Appendix.

Policy Landscape

Initiative	Sector	Region	Country	Implementation level	Completeness	Replicability
Virtual Power Plant (VPP)	Intersectoral	Asia	China	City level	●●○○	●○○○ Low
	Intersectoral	Oceania	Australia	National level / Regional level	●●●○	●●●○ Medium-High
Smart Mobility 2030	Transportations	Asia	Singapore	National level[13]	●●●●	●○○○ Low
SNCF (+RATP)	Transportations	Europe	France	National level / Regional level	●●●○	●●●○ Medium-High
Pavimenta2	Transportations	Latin America and The Caribbean	/	National level / Regional Level	●●●○	●●●○ Medium-High
AI-based Energy Optimisation in School Buildings	Buildings	Europe	Sweden	City level	●●●●	●●○○ Medium-Low
Policy-driven AI integration at Keppel Bay Tower	Buildings	Singapore	Singapore	National level	●●●●	●●○○ Medium-Low

[13] Note: Singapore is a city-state, thus policy implementation is simultaneously national and municipal in scope.

Conclusion

Building on the case studies presented in the report, several observations emerge.

In the building sector, HVAC systems can be considered an entry point for AI-enabled EE. Policy instruments to de-risk upfront costs are needed. For contexts where the data infrastructure is not yet in place, prioritising sensor rollout and BMS investment is the necessary first step before AI deployment can be considered. A structured approach to measuring AI's impact would clarify how these practices are evaluated and help inform future policy design.

In transportation, combination of multiple simple measures are prerequisite for an efficient system. Predictive maintenance could also be considered as a promising solution as it provides both economic benefits and improved EE.

The VPP cases go beyond technical aspects, showing that AI can develop within different institutional contexts with different levels of centralization. However, trade-offs exist: the most efficient systems tend to be less replicable, while more replicable ones often deliver weaker results. Ultimately, in these contexts, the effectiveness of AI for EE depends more on governance, infrastructure readiness, and incentive design than on technological sophistication alone.

Across the sectors, AI deployment depends on a sufficient level of digital infrastructure; investment in this area should therefore be treated as a prerequisite rather than a parallel effort. This comes with challenges related to data collection frameworks and data availability. Long-term investment in research and innovation is needed as well to address existing technological gaps.[14]

[14] More information on enabling factors on the adoption of AI for EE can be found in the Appendix, in section III. This section includes takeaways based on an interview with Mr. Laurent Mismacque, General Manager at Siemens.

Case Study 1: Shanghai – Virtual Power Plant (VPP)

Case Overview

In June 2025, Shanghai issued its Implementation Plan for User-Side Virtual Power Plant Construction[15], positioning the VPP as a solution to manage peak demand. The policy builds a 1+5 structure, including one VPP operation and management platform linked to five main urban resource categories[16]. Based on this national framework, Shanghai sets progressive targets from 1.1 million kW to 2.2 million kW of actual adjustable capacity in 2027.

How the System Works

The goal is to aggregate many small, distributed resources and operate them as if they were a single controllable power plant. It requires the platform to cover the full VPP chain—registration, connection, monitoring, dispatch, metering, and performance assessment—and to interface with grid dispatch and electricity market operations.

Its relevance to AI for EE lies in the system's digital layer: digital-twin models based on geographic and electrical data, graph computing for monitoring and early warning, and forecasting, simulation, and automated decision-support tools[17]. Although not branded as "AI," these functions are clearly data-driven, predictive, and automated.

This allows the city to adjust demand across buildings, EV infrastructure, storage assets, industrial users, and data centres when the grid is under stress, using existing loads more strategically across time and across sectors.

Completeness: 🔵🔵⚪⚪

Shanghai's VPP already has a formal municipal implementation plan, a defined governance framework, quantified capacity targets, technical access standards and a state evaluation framework. However, it does not yet look fully mature. The policy duration only runs from 2025 to 2027, the system is still expanding its market participation mechanisms and testing standards. The strongest evidence of real operation comes from a media coverage[18], which mentions that Shanghai completed its first million-kilowatt-scale VPP demand response operation, aggregating resources from 47 operators and reaching 1.163 million kW of load

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[15] Shanghai Municipal Government. Implementation Plan for User-Side Virtual Power Plant Construction (2025–2027). 2025. Accessed April 21, 2026.
https://www.shanghai.gov.cn/cmsres/32/3206eb41856440d3afae5f53f02d2749/2f9eb89e0bbda17668b8ab3d0802442d.pdf.
[16] ibid
[17] ibid
[18] China Daily. "Shanghai Breaks Record with Virtual Power Plant." August 13, 2025. Accessed April 21, 2026.
https://www.chinadaily.com.cn/a/202508/13/WS689c3e20a310b236346f1759.html.

adjustment when city demand hit 40.55 million kW[19]. This figure shows that the model is operating at a meaningful scale, but there are still early operational results.

Replicability: Low 🔵⚪⚪⚪

- Governance: 0/1
  Strong municipal coordination is key. The City government sets the framework, the grid company is tasked with building and operating the management platform and district-level authorities are folded into the same load-management mechanism. The policy plan explicitly emphasises unified management, dispatch and service, easier to implement under a centralised administration.

- Technical transferability: 0.5/1
  The architecture is transferable, but far easier to replicate in infrastructure-rich, digitally capable cities. Shanghai's VPP depends on high grid visibility and robust data systems, including interoperable digital platforms, resource-access standards, testing and certification mechanisms, and cybersecurity requirements.

- Economic accessibility: 0.5/1
  Shanghai's plan focuses on coordinating existing urban infrastructures more effectively, but still demands substantial investment in platforms, monitoring and control devices, digital upgrades, testing and maintenance. Price incentives, market-based subsidies and financial rewards linked to response capability and speed are also necessary, requiring sustained policy support.

- Knowledge requirement: 0.5/1
  The main challenge is not developing advanced AI technology. Shanghai's model requires competence in operational knowledge needed to integrate large numbers of heterogeneous resources into one functioning system. Making the whole socio-technical system work reliably at scale is a key factor that makes this policy successful.

[19] Evrim Ağacı. "Shanghai Breaks Record with Virtual Power Plant." 2025. Accessed April 21, 2026. https://evrimagaci.org/gpt/shanghai-breaks-record-with-virtual-power-plant-489272.

Case Study 2: South Australia – Virtual Power Plant (VPP)

Case Overview

The South Australia VPP was launched in 2018 as a collaboration between the South Australian Government and Tesla, and now is operated by AGL[20]. The project consists of a network of more than 6,500 homes equipped with solar panels and battery systems[21]. The initiative aims to expand further, with earlier programme targets reaching up to 50,000 installations[22].

How the System Works

The South Australia VPP aggregates household solar and battery systems through a digital platform that optimizes charging and discharging in response to grid and market signals. This coordination turns dispersed storage into a dispatchable asset that delivers peak demand relief and frequency services during grid disturbances[23]. Although policy documents do not explicitly frame the system as AI, its operational logic relies on data-driven optimisation and automated decision making. These functions allow the VPP to respond to real-time conditions and improve energy efficiency at the system level.

Completeness: 🔵🔵🔵⚪

The system has moved beyond the pilot stage and is functioning in practice, with thousands of households connected and active participation in grid operations. It has demonstrated measurable outcomes, including reduced energy costs for participating households and the ability to provide grid support services during system events.

However, the project has not yet reached full maturity. The intended scale of tens of thousands of households has not yet been achieved, and expansion is still ongoing. In addition, while operational performance has been demonstrated, long-term, independently evaluated systemwise impacts remain limited. The system can therefore be understood as operational but still in a scaling phase.

[20] Government of South Australia, Department for Energy and Mining. "South Australia's Virtual Power Plant." Accessed April 21, 2026. https://www.energymining.sa.gov.au/consumers/solar-and-batteries/south-australias-virtual-power-plant.
[21] ibid
[22] ibid
[23] Australian Energy Market Operator (AEMO). South Australian Electricity Report 2019. 2019. Accessed April 21, 2026. https://www.aemo.com.au/-/media/files/electricity/nem/planning_and_forecasting/sa_advisory/2019/2019-south-australian-electricity-report.pdf.

Replicability: Medium-low 🔵🔵⚪⚪

- Governance: 1/1
  The governance model of the South Australia VPP is relatively adaptable. It is based on collaboration between government, private energy companies, and households, and operates within a liberalised electricity market[24]. This makes it more compatible with decentralised governance systems compared to highly centralised models.

- Technical transferability: 0.5/1
  The technical model is moderately transferable. Solar panels, battery storage, and digital coordination platforms are the core components, which are widely available and increasingly standardised technologies.

- Economic accessibility: 0.5/1
  The model's economic accessibility is mixed. Its distributed structure enables gradual scaling and shared investment across households and private actors, but it still requires substantial upfront spending on solar and battery hardware. It also depends on public grants and concessional loans, which limits replicability in contexts with fewer financial resources or weaker public support.

- Knowledge requirement: 0.5/1
  The knowledge requirement for the South Australia VPP is relatively high. The system requires technical expertise in data analytics and energy system management, depending on continuous data collection and digital coordination across distributed assets. While end-users are not required to actively manage this system, operators must have the capacity to design and maintain the platform.

[24] Organisation for Economic Co-operation and Development (OECD). "South Australia's Virtual Power Plant." Accessed April 21, 2026. https://oecd-opsi.org/innovations/south-australias-virtual-power-plant/.

Comparison between the two selected case studies and the implications:

Dimension	Shanghai VPP	South Australia VPP
Governance Model	System-level optimisation across the entire urban grid	Device-level optimisation of household batteries
System Architecture	Highly centralised platform (1+5 structure)	Decentralised network of households aggregated via platform
EE Mechanism	Peak shaving and cross-sector load shifting	Self-consumption optimisation and battery efficiency
Role of AI	High (multi-sector integration: EVs, industry, buildings, data centres)	Moderate (primarily solar + battery systems)
Data & System Complexity	State-led, centrally coordinated	Market-based, public-private partnership
Implementation approach	Top-down expansion driven by policy	Bottom-up adoption driven by households and market incentives

The two models differ structurally. Shanghai's VPP uses top-down coordination to achieve cross-sector efficiency gains, but this makes it harder to replicate elsewhere. South Australia relies on a bottom-up model driven by households and market incentives, which is easier to scale but narrower in scope. The broader lesson is that there is no universal model for AI-enabled energy efficiency; effectiveness depends on institutional fit. Shanghai illustrates what system-level coordination can deliver, while South Australia demonstrates how participation can grow through simpler technologies and incentives. For policymakers, the key question is which approach can realistically work in their own context.

Case Study 3: Singapore – Smart Mobility 2030

Case overview

Singapore has one of the longest running AI programs applied to the transport sector. The Smart Mobility 2030 project[25] which started in 2014, provides a rare example of a fully deployed, nation-wide AI policy centered around EE in transports.

Singapore's structural constraints—limited land, no natural resources, and full dependence on energy imports—have pushed it to the forefront of AI applications for energy efficiency. With 6 million people living within 733 km^2, optimising energy use and transport flows is essential. This urgency drove major investments in "intelligent" transport technologies in the early 1990s, which later evolved into the Smart Mobility 2030 strategy led by the Land Transport Authority, where several of these systems have since developed into AI-based solutions.

How the system works

Smart Mobility 2030 is based on the creation of a real time digital map of traffic flows fed by a massive data collection system operated by the LTA, through GPS, cameras, sensors, and other means. The digital map is then analyzed and patterns are recognized to help operate different AI-based systems meant to reduce the overall energy consumption of the transport sector through traffic efficiency[26]. This is done through different AI-powered projects aiming to minimize cars' "stop-and-go" and related energy losses[27]:

- GLIDE, which optimizes traffic lights systems.
- EMAS, which minimizes traffic jams via camera and sensor street monitoring.
- CRUISE, which predicts congestion before it happens combining AI and GPS data.

Public transport scheduling is also optimized using AI, preventing unnecessary buses and trains from circulating with important energy savings.

The I-Transport platform is the platform that makes sense of all this data, processes it centrally and operates the systems mentioned above[28].

Completeness: 🔵🔵🔵🔵

Singapore's Smart Mobility 2030 plan is at Level 4 (Mature) of our Completeness scale:

[25] CHIN, Kian Keong, and Grace Ong. "Smart Mobility 2030 – ITS Strategic Plan for Singapore." n.d. Accessed April 21, 2026. https://pdf4pro.com/amp/view/smart-mobility-2030-its-strategic-plan-for-singapore-65ebae.html
[26] Sugihartono, Sekarsari. "Cities Embracing and Innovating AI Technology." Modern Diplomacy, August 3 2024. Accessed April 23, 2026. https://moderndiplomacy.eu/2024/08/03/cities-embracing-and-innovating-ai-technology/
[27] ITS International. "Singapore's LTA unveils ITS master plan" August 7, 2014. Accessed April 23, 2026. https://www.itsinternational.com/news/singapores-lta-unveils-its-master-plan
[28] Ivler, Joshua. "Future Cities - Singapore" ESGRELAB, January 28, 2025. Accessed April 23, 2026. https://www.esgrelab.com/post/future-cities-singapore

As of 2023, it is estimated that 80% of the traffic lights in Singapore are managed by AI systems[29]. The I-Transport platform is fully operational, and public transport AI scheduling has been running since 2020. This project is far from still being at the pilot or experimental stage. It has been part of the working infrastructure for some years now.

The results are encouraging at peak hour, the delays are reduced by 20%, the speed at rush hour increased by 3km/h (+15%). There has also been a 25% increase in public transport ridership since 2020[30]. There is no data that explicitly counts the amount of energy that is saved with the implementation of Smart Mobility 2030. However, the reduction in traffic, increase in average speed, and augmentation of public transport use suggests significant energy savings, estimating a saving of $1 billion annually for Singapore.

Replicability: Low 🔵⚪⚪⚪

- Governance: 0/1.
  Singapore's model depends on a centralized control of data collection and exploitation only possible in the context of a central governmental authority with the ability to mandate standards across the whole transport sector. These conditions are very difficult to reunite in Federal countries (United States, Germany), decentralized countries (France, Italy), or multi-authority transport systems (Paris: SNCF, RATP, etc.).

- Technical: 0.5/1.
  The underlying technologies (adaptative signal control, data collection tools, etc.) are not developed specifically by Singapore and can be bought (or developed) by any other city, region or country.

- Economic: 0.5/1.
  The AI components used by the LTA don't seem to be extremely expensive[31] (sensors, cameras, one central system to exploit them, etc.). However, they require infrastructure that Singapore has been investing in since the 1990s. Middle income countries and cities with a rather small transportation budget risk not being able to replicate the whole system quickly, although they can replicate some individual components (like adaptive traffic lights) at much lower cost.

- Knowledge : 0.5/1.
  Singapore is very scientifically advanced and has a lot of scientists working in the sector. It would seem like the policy is replicable in the countries that have research implemented on AI or at the very least computer programming for the parts of the program that are "intelligent" and not exactly AI.

[29] Dadang Irsyam. "Driving the Future: How AI Is Powering Singapore's Smart City Vision for 2030". Medium, October 6, 2024. Accessed April 23, 2026. https://medium.com/@dirsyamuddin29/driving-the-future-how-ai-is-powering-singapores-smart-city-vision-for-2030-7d371db705fd
[30] ibid
[31] Based on the elements that I managed to find about the costs of the research

Case Study 4 : France – SNCF use of AI

Case overview

France's SNCF is Europe's second largest railway network, providing it exceptional scale for implementation of AI-powered EE systems.

France's electricity production comes mostly from nuclear energy (70%), making the railway systems, mainly electricity dependent, almost decarbonized. The interest of EE policies in the railway systems in France is thus purely about energy savings and cost reductions.

SNCF is a public industrial and commercial establishment, which means they have general governmental guidelines to follow but keep significant operational autonomy. This allows SNCF to dedicate about 5% of its revenue every year for digital transformation, which includes AI technologies for EE[32].

SNCF's strategy started integrating AI in its IT systems in 2010[33] and has put a specific emphasis on AI development in the past three years, partnering with Mistral AI[34] and Ecole Polytechnique[35].

How it works

- The main AI tool for EE developed by the SNCF is Opti'Conduite[36]. This AI-powered eco-driving assistance system works as an addition to existing trains and gives conductors instructions in real time while maintaining high speed objectives.
- Stations have also become a target to improve EE via AI, automatically adjusting resource consumption to factors such as temperature, affluence, behaviour of passengers or emergencies[37].
- SNCF also uses predictive maintenance[38] by improving trains and rails performance thanks to extensive data collection, with positive outcomes for EE [39].

[32] ActuIA. "SNCF Revamps Its Digital Governance to Accelerate AI Integration" ActuIA, April 19, 2025. Accessed April 23, 2026. https://www.actuia.com/en/news/sncf-revamps-its-digital-governance-to-accelerate-ai-integration/
[33] Dumitru, Andrei. "SNCF Group and Mistral AI Form Strategic Partnership". Railway PRO, June 19, 2025. Accessed April 23, 2026.
https://www.railwaypro.com/wp/sncf-group-and-mistral-ai-form-strategic-partnership/
[34] SNCF Group. " SNCF Launches AI Research Program at the École Polytechnique" September 16, 2024. Accessed April 23, 2026.
https://www.groupe-sncf.com/en/innovation/emerging-technologies/ai-research-program-polytechnique
[35] ibid
[36] ActuIA. "SNCF - Artificial Intelligence". ActuIA, n.d., Accessed April 21, 2026.
https://www.actuia.com/en/actors/sncf/
CAFFA, Harry. "Keynote Numérique groupe SNCF". SNCF NUMÉRIQUE, 2024. Accessed April 23, 2026.
https://numerique.sncf.com/actualites/keynote-numerique-groupe-sncf/
[37] ActuIA. "SNCF - Artificial Intelligence". ActuIA. Accessed April 21, 2026. https://www.actuia.com/en/actors/sncf/
[38] SNCF Voyageurs. "Keeping pace with innovation" 2024. Accessed April 23, 2026.
https://www.sncf-voyageurs.com/en/our-company/divisions-and-subsidiaries/rolling-stock-division/our-stakes/innovation/

[39] SNCF Group. "Financing the Future of Rail: A Priority for France and Its Regions" May 5, 2025. Accessed April 23, 2026. https://www.groupe-sncf.com/en/group/strategy/sncf-group/priority-investment-in-french-regions

This system was replicated by the RATP[40], Paris' urban transport operator, demonstrating its success.

Completeness: 🔵🔵⚪⚪

SNCF's AI strategy seems to be situated between the 2/4 Pilot stage and the 3/4 Operational stage. Some of the equipment seems to have been in place for some years and seem to indicate good performance on EE, despite a pretty striking lack of data concerning the actual efficiency. Some AI tools however, are still at the Pilot stage, like the tools necessary for the stations' efficiency, which have only been implemented in some stations, without concluding results so far.

Replicability: Medium-High 🔵🔵🔵⚪

- Governance: 1/1
  Independent of governance, can be applied to public systems and private systems alike.

- Technical: 0.5/1
  The technologies used don't seem to require extensive technical bases. They don't require new trains, new railways, or new stations, just simple additional AI-based technologies.

- Economic: 1/1
  The AI components used by the RATP don't seem to be extremely expensive. Their rather recent implementation suggests that it doesn't require years of previous investments for AI.

- Knowledge : 0.5/1
  France does have the advantage of being very advanced in the tech sector, as suggested by its partnerships and many AI companies but the technologies don't seem too difficult to implement.

[40] RATP Group. "Innovating for Better Mobility and Services Tomorrow." n.d., Accessed April 21, 2026. https://ratpgroup.com/en/commitments-and-innovations/industrial-and-technical-innovation/

Case Study 5: Latin America and the Caribbean - Pavimenta2

Context

Surface roughness affects vehicle energy efficiency, as poor road conditions increase energy use.[41] To optimize time on data collection and maximize expertise, the Inter-American Development Bank (IDB) developed an AI-based tool, Pavimenta2, to run data collection and data analysis for the Latin America and The Caribbean region. In the last 5 years, Pavimenta2 automates detection and analysis of pavement conditions, thereby enabling more effective road maintenance planning. Although this is not its primary objective, Pavimenta2 contributes to improve EE by enhancing road quality and reducing the need for maintenance interventions. Pilot projects have been conducted in several Latin American countries[42].

How the system works

Images are collected using a smartphone or a GoPro® camera mounted on a vehicle driving along the road network. The images are further processed to remove duplicate detections and to convert measurements from pixels into meters. Computer vision models, a subfield of AI, analyse these images to detect and map road distresses. All images are geolocated using GPS data, allowing precise spatial mapping of detected defects.[43]

Completeness: 🔵🔵🔵⚪

The application is fully operational and has been made available through the IDB software library, where it can be deployed and further enhanced. As mentioned earlier, the tool has been in use for the past five years across different countries in the region, but is not fully generalized in the region.

Replicability: Medium - High 🔵🔵🔵⚪

- Governance : 0.5/1
  Pavimenta2 is accessible and can be implemented and managed by various institutions at national or regional levels. Implementation mainly requires partnerships with

[41] Asociación Española de la Carretera (AEC). "*Análisis de la relación entre el estado de conservación del pavimento, el consumo de combustible y las emisiones de los vehículos*." December 12, 2019. Accessed April 23, 2026. https://www.aecarretera.com/comunicados/Incremento%20emisiones%20C02%20carretera%20en%20mal%20estado.pdf

[42] "AI and Deep Learning for Identifying Pavement Failures in Latin America and the Caribbean." Global Infrastructure Hub. Last modified October 21, 2022. Accessed April 23, 2026. https://infratech.gihub.org/infratech-case-studies/ai-and-deep-learning-for-identifying-pavement-failures-in-latin-american-and-the-caribbean/

[43] "Pavimentados." Inter-American Development Bank. YouTube video, March 3, 2023, 20:01. Accessed April 23, 2026. https://youtu.be/m3KsdkTqzg0

transport agencies. The integrated data collection process raises no significant governance or legal issues.[44]

- Technical transferability: 1/1
  The tool is suitable for countries with low levels of technological infrastructure. Data collection requires a simple camera. Limited internet connectivity is not an issue, as the images can be recorded offline and processed later.[45]
  It is an open-source solution based on widely used and standardized technologies such as Python, TensorFlow, and YOLO models.[46]
  It requires minimal cloud infrastructure.

- Economic accessibility: 1/1
  The IDB initially invested in the development of this open-source tool available in their database. Its current use does not require significant financial investment and it can allow for significant economies in comparison to traditional road assessment methods.

- Knowledge requirement: 0.5/1
  Some adaptation may be necessary depending on local IT infrastructure, requiring support from technical staff.[47]

[44] "AI and Deep Learning for Identifying Pavement Failures in Latin America and the Caribbean." Global Infrastructure Hub.
[45] "Pavimentados." Inter-American Development Bank. Youtube Video.
[46] "Pavimentados." Inter-American Development Bank. Accessed April 19, 2026. https://knowledge.iadb.org/en/open-knowledge/code-development/open-source-solution/pavimentados
[47] "AI and Deep Learning for Identifying Pavement Failures in Latin America and the Caribbean." Global Infrastructure Hub.

Case Study 6: Sweden – AI-based Energy Optimisation in Stockholm School Buildings

Case Overview

Buildings account for 37% [48]of energy consumption globally, and Heating, Ventilation and Air Conditioning (HVAC) systems alone account for 40[49]–60%[50] of that consumption. This case study shows one successful example of how AI came into use to address this[51].

How the System Works

SISAB (Skolfastigheter i Stockholm AB) is a municipally owned company responsible for managing ~600 school and preschool buildings in Stockholm. It consumes over 250 GWh energy annually at a cost of €29.4 million, which made energy reduction both a financial and environmental[52] priority. To achieve this, it has deployed a Building Management System (BMS) and more than 20,000 temperature and CO_2 sensors by 2020.

The AI system[53] developed with Myrspoven and Schneider Electric was built on this data infrastructure. AI plus data has enabled the HVAC adjustments every 15 minutes to match actual conditions more closely and cut avoidable energy use.

Over the period 2019–2023, district heating consumption decreased by 3.12% and electricity use by 8.93% across the 87 buildings being tested. Notably, the evaluation accounts not only for energy savings but also for the emissions and hardware costs associated with the AI system, reporting a carbon benefit-to-cost ratio exceeding 1:240.

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[48] World Bank. Achieving Energy Efficiency in Buildings. Washington, DC: World Bank, 2025. https://openknowledge.worldbank.org/entities/publication/1f57171a-f68f-47ed-99b5-edd917a320cb.
[49] Pérez-Lombard, Luis, José Ortiz, and Christine Pout. 2008. "Energy Consumption Information in Buildings." Energy and Buildings 40 (3): 394–398. https://doi.org/10.1016/j.enbuild.2007.03.007. (50%)
[50] Cuce, Pinar Mert, and Erdem Cuce. 2026. "Role of HVAC in Building Energy Consumption: A Critical Review." Journal of Thermal Analysis and Calorimetry 151: 3059–3080. https://doi.org/10.1007/s10973-026-15322-9. (40-60%)
[51] Smart City Sweden. "Optimizing Energy Use in Schools with Real-Time Data and AI." Accessed April 21, 2026. https://smartcitysweden.com/best-practice/446/optimizing-energy-use-in-schools-with-real-time-data-and-ai/
[52] European Commission. 2025. "Stockholm Unveils Ambitious Climate Action Plan for 2030 – Setting a Bold Example as the First European Green Capital Awarded in 2010." May 21, 2025. https://environment.ec.europa.eu/news/stockholm-unveils-ambitious-climate-action-plan-2030-setting-bold-example-first-european-green-2025-05-21_en.
[53] Paccou, Rémi, and Gauthier Roussilhe. 2024. AI-Powered HVAC in Educational Buildings: A Net Digital Impact Use Case. Schneider Electric. https://myrspoven.com/wp-content/uploads/2024/12/TLA_AI_Powered_HVAC.pdf.

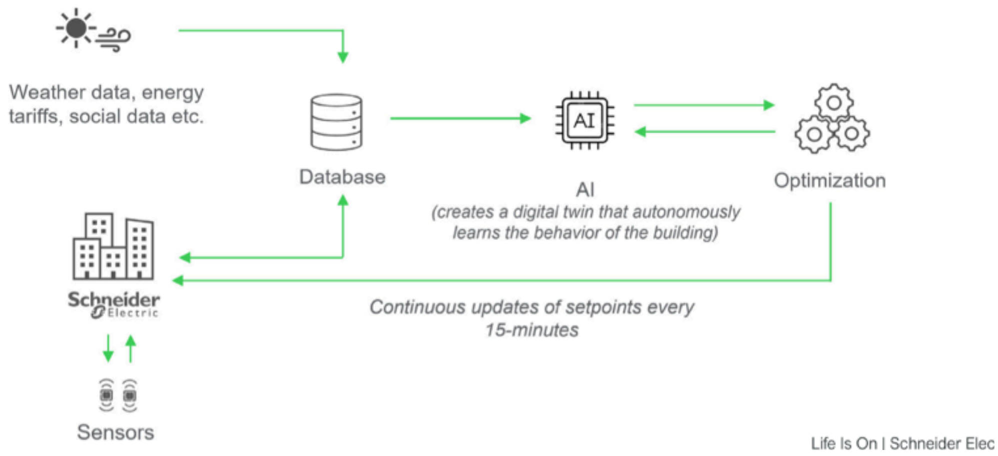

Illustration of the data flows between the AI-Powered solution and the BMS.
Source: Schneider Electric

Completeness: 🔵🔵🔵🔵

This case is mature with results accounting for both energy savings and the carbon cost of the AI system itself, following a publicly auditable methodology.

Replicability: Medium-low 🔵🔵⚪⚪

- Governance: 0.5/1
  The model relies heavily on SISAB's centralized structure which removes the owner–tenant split and aligns incentives for energy savings. Implementation would be complex in contexts with more fragmented ownership and operational responsibilities.

- Technical transferability: 0.5/1
  The system builds on an extensive existing data infrastructure. In contexts without comparable sensor coverage or interoperable systems, replication would require substantial upfront investment before any AI layer could be deployed.

- Economic accessibility: 0.5/1
  The solution has a projected payback period of under 3 years. As a cloud-based service, large capital expenditure is not needed. Implementation was also financed through standard municipal budgets rather than bespoke funding schemes.

- Knowledge requirement: 0.5/1
  The system processes around one million data points per day and relies on continuous model optimisation, supported by centralised operational expertise. Organisations without similar data management capacity and technical expertise would face a significant barrier to replicate.

Case Study 7: Singapore – Policy-driven AI integration at Keppel Bay Tower

Case Overview

As Singapore's first commercial building to receive Green Mark Platinum Zero Energy certification — the highest tier in the scheme, Keppel Bay Tower (KBT), an asset of Keppel Land, underwent a five-technology[54] retrofit between 2018 and 2020, supported by public funding from BCA's Green Buildings Innovation Cluster (GBIC) programme.

The impact was significant. KBT achieved energy savings of ~30% (~2.2 million kWh) over the measurement period[55] compared to the baseline. Its energy efficiency improved by 20% [56]compared to other BCA Green Mark Platinum buildings.

How the System works

KBT adopted a machine learning-based fresh air control system developed by Yitu, uses sensor data including CO_2, temperature, and occupancy to adjust fresh air intake, and a physics-based intelligent building control system developed by IES[57], which relies on a physical model of the building to manage performance and adjust system settings. Occupancy and air quality data from Yitu feeds into the IBC's control decisions. This AI model updates as it accumulates more data from the building.

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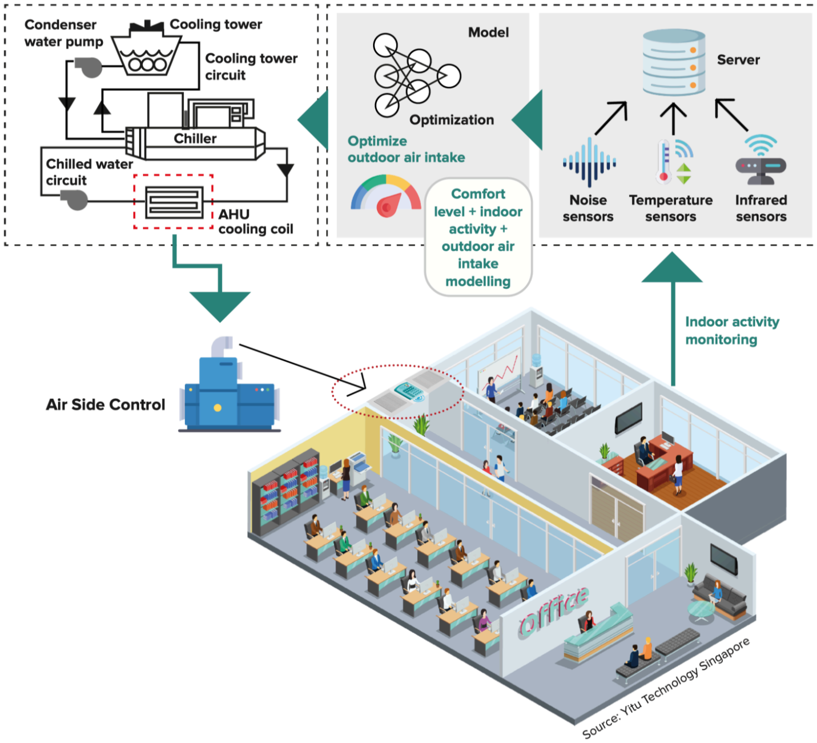
[54] World Cities Summit. "WCS 2021 Virtual Site Visit: Keppel Bay Tower." YouTube video. Accessed April 21, 2026. https://www.youtube.com/watch?v=f0Tz2ON6ECY.

[55] Building a Sustainable Future, Sustainable Report 2024, Keppel ltd. https://www.keppel.com/file/sustainability/sustainability-reports/keppel-ltd-sustainability-report-2024-full-report.pdf.

[56] Keppel Bay Tower: Singapore's First Green Mark Platinum (Zero Energy) Commercial Building, Keppel Ltd., Accessed April 21, 2026. https://www.keppel.com/realestate/Special-Features-Library/Keppel-Bay-Tower-a-green-building-of-the-future.

[57] IES, Keppel Bay Tower: Calibrated Energy Modelling, https://www.iesve.com/icl/case-studies/34237/keppel-bay-tower.



Source: Keppel, ltd.

Completeness: 🔵🔵🔵🔵

This project is mature with the goal achieved and even exceeded: By February 2020, KBT had achieved a 22.3% reduction in annualised energy consumption, exceeding the initial 20% target set under the GBIC programme.

Replicability: Medium-low 🔵🔵⚪⚪

- Governance: 1/1
  Green Mark [58] system provided market signal for building owners to capture value. GBIC Programme[59] reduced the upfront financial risk for piloting emerging technologies. Green leases further helped align incentives between KBT and tenants with ESG reporting needs (KBT achieved 100% [60]participation for office tenants in signing green leases). This

[58] Singapore Building and Construction Authority. "Green Mark Incentive Scheme for Existing Buildings 2.0 (GMIS-EB 2.0)." Accessed April 21, 2026. https://www1.bca.gov.sg/grants-and-funded-programmes/green-mark-incentive-scheme-for-existing-buildings-2-0.
[59] Singapore Building and Construction Authority. n.d. "Green Buildings Innovation Cluster (GBIC) Programme." Accessed April 21, 2026. https://www1.bca.gov.sg/sustainability/green-buildings-innovation-cluster-gbic-programme/.
[60] Keppel Bay Tower: Singapore's First Green Mark Platinum (Zero Energy) Commercial Building, Keppel Ltd., Accessed April 21, 2026. https://www.keppel.com/realestate/Special-Features-Library/Keppel-Bay-Tower-a-green-building-of-the-future

multi-layer incentive does not necessarily depend on a centralised authority, which increases the replicability.

- Technical transferability: 0.5/1
  The model is presented as applicable to other commercial buildings. The approach still depends on the presence of a BMS and the ability to coordinate multiple technology providers.

- Economic accessibility: 0.5/1
  The project received SGD 1.28 million in public funding through the GBIC programme for pilot phase. Green leases also shift part of the responsibility for energy reduction to tenants, without requiring additional public funding. Although the payback period is not clearly stated, where commercial property markets are active and building owners are responsive to financial incentives, a similar funding structure could work without requiring unusually large public budgets.

- Knowledge requirement: 0/1
  The project required coordinating five specialist technologies across machine learning, simulation, mechanical engineering, and system integration simultaneously. In contexts where the relevant technical expertise is less readily available, assembling a comparable multi-vendor programme would present a significant barrier.

Comparison between the two selected case studies and the implications:

Case	Singapore – KBT	Sweden – Stockholm SISAB SOLIDA
Location + climate	Tropical climate: year-round cooling demand; HVAC ≈ 50% of building energy.	Cold climate: heating-dominated; HVAC 30–50% of building energy.
Building type	18-storey commercial office tower (built 2002), 394,000 sq ft, multi-tenant.	87 schools (preschool to college), 100–48,000 m², building age 7–15 years, single municipal operator.
Role of AI	Machine learning-based HVAC optimisation, integrated as one of five enabling technologies in a broader retrofit programme; AI contribution is difficult to isolate from the combined effect of all five systems.	AI is the sole intervention, acting as a virtual building operator to adjust HVAC setpoints every 15 minutes.
Funding/ Financial Incentives	SGD 1.28 million GBIC government grant for five-technology pilot. Green leases signed by 100% of tenants (committing to 5% energy reduction). Payback period not stated in source.	Municipal budget. Projected payback period <3 years (assessed at time of 2018 selection). Energy cost savings eligible for reinvestment; specific reinvestment allocation not quantified in source.

The two cases provide different but complementary takeaways.

The Singapore case shows how market incentives can be built into a policy tool. Green Mark certification sets verifiable performance targets while generating commercial value for building owners. GBIC grants shift the financial risk of piloting emerging technologies from firms to the public sector. Green leases address the landlord-tenant split through contractual rather than regulatory means. Together, these tools suggest that existing certification and funding structures can be extended to incorporate AI performance criteria without requiring entirely new policy architectures.

The Stockholm case illustrates a different pathway: SISAB's role as both owner and operator, directly managing energy bills, allowed policy goals, operational incentives, and technical capabilities to align without market instruments. Multi-level governance climate targets created a stable policy environment for investment. The project also applied a structured approach to measuring AI's impact, including the carbon cost of the technology itself, offering clearer evaluation methods for AI in practice.

Even when under radically different climates, HVAC systems represent a consistent entry point for AI-enabled EE in buildings. Both cases also relied on existing sensor networks and BMS. This suggests that AI deployment depends on a prior level of digital infrastructure.

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Appendix

I. Detailed Replicability Scale:

For the following 4 parameters, assign 0 points for hard replicability; assign 1 for easy replicability.

- Governance fit: How much does this policy depend on specific governance structure?
  - +1 for easy replicability : works in decentralized multi-actor contexts; low to moderate amount of data required;
  - +0 for hard replicability: requires small, unified, top down government,high amount of data required; might infringe privacy laws in other constituencies;

- Technical transferability: how dependent is the technology/ policy on existing infrastructure that isn't present in every country?
  - +1 for easy replicability: uses standard AI tools, standard data collection tools, open data.
  - +0 for hard replicability: requires advanced existing IT infrastructure, very dense sensor systems.

- Economic accessibility: what level of public investment is necessary?
  - +1 for easy replicability: low cost, scalable incrementally
  - +0 for hard replicability: requires massive investments or unique partnership that is difficult to replicate in every country

- Knowledge requirement (how much knowledge needed)
  - +1 for easy replicability: requires short trainings, non-technical profiles; low to moderate amount of data required
  - +0 for hard replicability: requires highly specialized workforce high amount of data required; might infringe privacy laws in other constituencies

II. Interview with the expert: enabling factors and policy takeaways

Which enabling factors do we need to fully take advantage of the AI revolution for energy efficiency? What is limiting the uptake of AI for Energy Efficiency? The following box provides an overview of the underlying challenges and potential levers for policymakers provided by an exchange with Laurent Mismacque, practitioner from the field.

The lack of comprehensive public policies to regulate and support the use of artificial intelligence (AI) for energy efficiency in buildings and transportation is strongly linked to the limited adoption of AI technologies by individual enterprises.

Based on insights from an interview with **Mr. Laurent Mismacque,** General Manager, Customer Digital Services, Siemens, the key levers, and challenges for scaling this promising technology are summarized below.

Low adoption levels of AI for energy efficiency reflect broader structural challenges that affect the uptake of AI technologies more generally. Three major barriers to large-scale AI adoption and deployment were identified:

- A lack of systematized collection of high-quality data to train and operate AI systems
- Uneven and uncoordinated levels of digitalization within the same site, organization, or infrastructure
- Skills shortages and mismatches, particularly the lack of data scientists and AI-trained profiles

In addition, fully leveraging AI for energy efficiency requires AI solutions that are explainable, frugal, and effective.

Explainability refers to the ability of humans to understand and interpret the decisions and analytics produced by AI systems.
Frugality implies ensuring that AI solutions consume less energy than the systems they are designed to optimize. In this regard, edge computing—rather than purely cloud-based AI—represents a key opportunity to reduce energy consumption.
Finally, **effectiveness** depends on system-wide adoption and seamless integration, rather than the deployment of AI on isolated components or individual subsystems.

To scale AI adoption and unlock its full potential for energy efficiency, decision-makers should integrate the following levers into public policies:

- Harmonization of standards and protocols for AI-enabled hardware (e.g., smart thermostats)
- Promotion of open standards to enable interoperability across systems
- Creation of incentives based on results-driven and sustainability-driven performance (e.g., CO_2 avoidance)