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A review of methods to analyze technological change in industry

D.A. Toribio-Ramirez [a,b,*], B.C.C. van der Zwaan [a,b,c], R.J. Detz [a], A. Faaij [a,d]

[a] TNO Energy and Materials Transition, Amsterdam, the Netherlands
[b] University of Amsterdam, Faculty of Science (HIMS), Amsterdam, the Netherlands
[c] Johns Hopkins University, School of Advanced International Studies (SAIS), Bologna, Italy
[d] Department of Science, Technology and Society, Copernicus Institute for Sustainable Development and Innovation, Utrecht University, Utrecht, the Netherlands

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ABSTRACT

There is an urgency to accelerate the innovation, development, and deployment of low-carbon industrial processes. Reviewing existing insights into how to achieve rapid technological change may be useful to assist this acceleration. Literature offers a set of approaches to model learning-by-doing and cost reductions, such as the learning curve methodology. However, it is debated if it can accurately describe and project cost reductions for low-carbon industrial processes. The goal of this work is threefold. First, to give more insight into what factors may explain the speed of innovation and technological change of low-carbon energy technologies. Second, to review existing approaches to model innovation and technological change of energy technologies and industrial processes. Third, to devise a framework to study technological learning of industrial processes. This work presents three main outcomes. First, we report more than 30 barriers and drivers of technological change. Second, we present a list of learning curve models and complementary methodologies to represent and/or explain these barriers and drivers. Third, we propose a framework to model technological learning of low-carbon industrial processes.

1. Introduction

Strategies to reduce greenhouse gas emissions need to be quickly implemented in all economic sectors to achieve the net zero-emission targets for 2050 implied by the Paris Agreement [1]. Low-carbon technologies in the electricity sector, such as solar PV and wind turbines, are rapidly being deployed and thereby have experienced significant cost reductions. However, the power sector is not yet on track to achieve a successful energy transition. The industrial sector is running even further behind, mainly due to the high cost of low-carbon processes, which hinders quick deployment. Technologies for decarbonizing industry require assistance to boost their innovation process, reduce costs, and achieve rapid deployment [1–3].

Given the current situation and the short time horizon to achieve the industrial transition, there is an urgency to accelerate innovation and technological change in industry and transform the existing energy sector by implementing low-carbon technologies. A first step to accelerate innovation and technological change in industry might be to better understand how these processes occur for low-carbon technologies in the energy sector. If the factors that drive or hamper innovation are identified, and their effect is understood, then it may be possible to accelerate and give direction to the transition towards a sustainable energy system [4,5].

Literature offers various methodologies to analyze technological change. A learning curve (LC) is an approach used to quantitatively describe and project the effects of learning on the costs of a technology. A one-factor learning curve (OFLC) is obtained by plotting the cost per unit produced (or any other chosen performance metric) against an experience metric, for example, the cumulative installed capacity (CIC). The OFLC approach assumes that the technology cost will decrease by a certain percentage with each doubling of the experience metric. This percentage is known as the learning rate (LR) [6–9].

LCs have been used to understand cost reductions of solar PV and wind turbines but have not been widely used for studying industrial processes. Applying the LC approach to analyze cost reductions of low-carbon industrial processes is likely further complicated. This is due to the large portfolio of options that may contribute to achieve industrial decarbonization. For example, different improvements can be installed in existing processes, new low-carbon feedstock and materials may be used, or new low-carbon technologies may be implemented. To study the technological change of a single process, consideration has to be given to e.g., different technologies, functional units, development stages, and unit sizes. Furthermore, data availability might be also an

* Corresponding author. TNO Energy and Materials Transition, Amsterdam, the Netherlands.
E-mail address: d.a.toribioramirez@uva.nl (D.A. Toribio-Ramirez).

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List of abbreviations

2FLC	two-factor learning curve
CIC	cumulative installed capacity
FIS	functions of innovation system
FP	formative phase
LBS	learning-by-searching
LC	learning curve
LBD	learning-by-doing
LR	learning rate
MCLC	multi-component learning curve
MFLC	multi-factor learning curve
OFLC	one-factor learning curve
R&D	research and development
TIS	technology innovation system

issue. If not enough historical performance and experience data is available, other solutions might be needed to perform an LC analysis. Additionally, the expansion capacity of energy intensive industrial processes might be limited. This may hinder the application of LCs, because if the experience parameter is not doubling, a mistaken conclusion that the system is not learning might be drawn.

The aim of this work is threefold. The first goal is to conduct a comprehensive literature review of the factors that may explain the speed of innovation and technological change of low-carbon energy technologies. As part of the review, a data analysis is performed to provide more insight into the nature of technological change and evaluate the aptitude of LCs to represent it. The second goal of this work is to draw a set of better practices for modelling innovation and technological change, as well as to determine the adequacy of the LC approach to represent technological innovation and learning. This is achieved by finding existing methodologies to analyze innovation and technological change of energy technologies, giving special attention to the LC approach. The novelty of this research lies on the creation of a framework to study technological learning of low-carbon industrial processes. This framework can be applied to the large variety of industrial decarbonization options and can be used to identify the main potential sources of cost reduction. This may give more insight into the actions to be taken and goals to target to accelerate cost reductions.

Section 2 presents a conceptual survey of the current state-of-the-art of the LC approach, as well as of the existing models in literature to describe technological learning of energy technologies and industrial processes. Section 3 reviews the existing literature on drivers and barriers of innovation and technological change. Section 4 shows a data analysis of existing learning rates of energy technologies and industrial processes. Our overall results are presented in Section 5. A set of final remarks and recommendations for future research is presented in Section 6.

2. Conceptual review of the learning curve approach

A comprehensive review was conducted using Elsevier and Google Scholar. Key words such as 'learning curve', 'technological learning', 'technological change', and 'technological innovation' were used to find relevant studies from 2000 to 2023. The search included peer-reviewed journal articles, as well as books and reports from the International Energy Agency, and other relevant organizations. A total of 17 800 papers were found in Google Scholar. We first focused on the most relevant and recent studies, as well as existing review articles [6,7,9–22]. Most of these focus on gathering LRs from literature, summarizing the methodological limitations of OFLCs, presenting existing methods to address such shortcomings, and addressing the application of LRs in energy system models. Further review of work cited in the initial set of papers extended our set of studies. Fig. 1 shows the various efforts to review findings on the LC approach and its application for modeling cost reductions of energy technologies.

2.1. The learning curve theory and previous reviews

While it is true that the OFLC can be a useful tool to quantitatively evaluate technological change, literature reports several pitfalls to this method. One of the criticisms made is the fact that it originates from empirical observations and is not an actual principle [18]. Thus, its reliability and capacity to properly explain and project the relationship between performance and experience might be hindered. However, it has been proven that in various cases, this relationship does apply to a great number of technologies [23]. To test if there is indeed a correlation between the variables under study, the correlation coefficient (R^2) may be calculated. This number can take values between 0 and 1. A higher R^2 means that there is a strong correlation between the dependent and independent variable [9]. Nevertheless, even if there is a statistical correlation between the performance and experience, there might not be any causality between these two variables.

Another recurrent criticism is that it assumes that all the cost reductions are uniquely caused by experience gained by doing. There might be other factors that cause or contribute to the observed cost reductions [14]. Ignoring these, might result in the overestimation of the learning effect (also known as the omitted variable bias). This means that the LR is biased upwards, because there are other variables, which are not considered in the model, but are in fact affecting the performance [24]. Also, the fact that OFLCs are highly aggregated and consider just one cost reduction factor, disregards other sources of knowledge and experience, and hinders its ability to give insight into the complex dynamics that occur in the learning process [21]. A possible solution to address the aggregation issue of the OFLC is to use a multi-factor LC (MFLC) or a multi-component LC (MCLC). Both are extended models, which include various cost reduction factors/components in order to better understand the different cost reduction mechanisms [25]. A deeper explanation of these models is presented in Section 2.2. Junginger et al. [23] recommend studying the causes of past reductions and the possible future opportunities before building the LC. Samadi [18] gives three suggestions to better model cost reductions. First, to consider the different sources of cost reduction that can be present. Second, to study individual learning systems by means of study cases. Lastly, to consider if past learning also plays a role in observed cost reductions. Moreover, Elia et al. [21] present a framework to give a better idea of which factors should be considered for an LC model depending on the technological development stage. Likewise, in order to address the omitted variable bias, Santhakumar et al. [20] suggest using logistic growth curves to include other cost reduction effects in the model. They also advise to use bottom-up models to help identify and better understand the existing cost reduction drivers.

Another frequent point of discussion is whether it is possible to assume that the LR is a constant term or not [14]. There are multiple examples which show that the LR stays constant throughout the technology's development stages and consider it to be adequate to assume a constant value. However, others state that because of market saturation, the LR value may decrease as the technology matures. This is because it might be more difficult to double the CIC once the market is more saturated [11,23]. Ferioli and van der Zwaan [26] observe that the LR may not be constant, because it depends on both, cost reductions and technological growth trends. Also, they argue that the LC might only be apt to model the initial technological development stages, when these two trends have an exponential behavior. Moreover, the fact that in the past, certain costs reductions have been observed, does not mean that these will also occur in the future. As referred by Söderholm and Sundqvist [27], using historical LRs to try to predict future cost reductions might be a wrong practice. This is because new factors, which might have a determining effect on the LR, may be ignored.

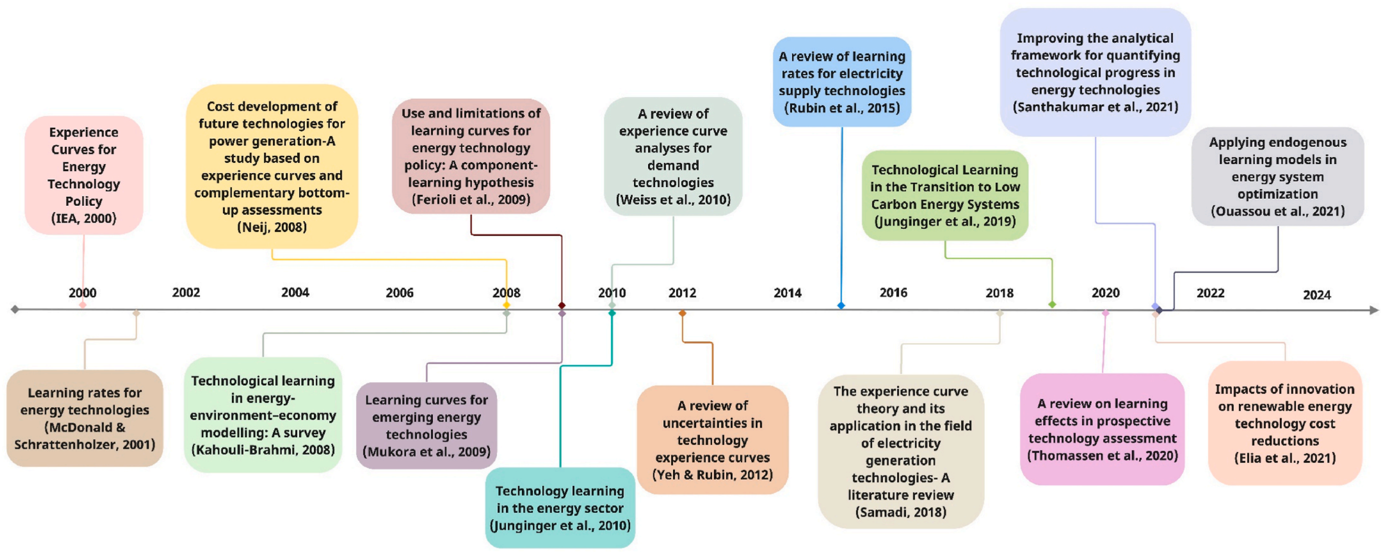


Fig. 1. Timeline of literature reviews on learning curves for energy technologies.

Variations of the LR between different technologies, but also among the same technology type have been reported in literature [17]. Variability and uncertainty in the LR value may come from various sources. First, uncertainty may arise from data recovered during the first years of development, since the process is still not well stabilized. To address this issue, Samadi [18] suggest making a conscious effort to find and include reliable historical data. Additionally, Junginger and Louwen [9] make a summary of the most common data availability issues and possible solutions to consider. Second, when production cost data is unavailable, market prices need to be used as proxy of the performance parameter. If this happens, then the relationship between costs and prices during the period under study must be discussed, and, if possible, one must correct the values. The approach presented by the Boston Consulting Group relating cost and prices during the first innovation stages might be used. For a deeper explanation of this subject, referrer to Refs. [6,23] or [20]. Other sources of uncertainty and variability proposed in literature are: the selected starting cost for a technology, the technological development stage, the amount of data-points used, the use of different data-sets and econometric techniques, the conceptualization of the learning system (e.g. time boundaries, performance parameter, geographical area), experience depreciation (also known as forgetting), cost reduction factors included in the model, and inflation or exchange rate used in the analysis may also cause uncertainty and variability [27–29].

Söderholm and Sundqvist [27] present a set of recommendations to select or determine a LR. First, to use a sensitivity analysis to test the impact of using less observations from the data sample, and different performance parameters. Then, to consider scale effects in the analysis, as well as the effects of other cost reduction factors. Next, to check for simultaneity in the LR estimations since diffusion and innovation are not independent variables. Finally, to use a time trend test, to assess the robustness of the results obtained. Weiss et al. [15] also make five suggestions to have a reliable LR estimate. First, to use error margins of the LR to show the results with uncertainty intervals. Second, to use more data points to determine the LR. Third, to supplement the LC approach with other tools to get qualitative information and confirm the observed cost reductions and price dynamics. Fourth, to use and develop more sophisticated models for describing the process of technological learning. Finally, to use disaggregated cost indices to correct price and cost estimates.

To address some of the OFLC pitfalls integrated frameworks have been developed. For example, an analytical framework is presented by Neij [10], which consist of three methods: LCs, bottom-up analysis, and expert assessment. The first step is to determine a LR. Then, the bottom-up analysis is used as a complementary tool to identify the sources of cost reduction in the short, and midterm and give more robustness to the LRs found. Finally, the expert assessment helps to give more insight to expected long term cost reductions. As part of the framework, uncertainty ranges of ±2 % and ±5 % are included for each LR to account for small and large uncertainties, respectively. Santhakumar et al. [20] present a framework to model technological learning. The first step is to identify the development stage of the new technology. Depending on the development stage and the expected data availability, a certain LC model is recommended to make the analysis. Additionally, this framework also suggests three other methodologies, which can be simultaneously applied to overcome the limitations of the LC method, namely bottom-up cost modeling, technology diffusion curves, and methods to qualitative describe technological learning. It is suggested to further apply these approaches to test its limitations and uncertainties.

The LC can be modified to include the effects of previous experience (Stanford-B model), automation (De Jong's model), and forgetting, among other effects [30,31]. The last refers to the decline in performance that may happen over time. Some of the sources of forgetting reported in literature are frequent interruptions in the production process, the time these interruptions lasted, changes in the product's specifications, or knowledge depreciation [32,33]. Forgetting has been modeled as a function of different factors, like worker's previous experience, cumulative operation time, the learning rate, and the worker's performance after the learning process. These forgetting models are mostly used in the industrial engineering and operations management discipline. A more in-depth review of forgetting models can be found in Ref. [34].

2.2. Modeling innovation and technological change of energy technologies

2.2.1. Two-factor and multi-factor learning curves

An alternative model to the OFLC is the two-factor LC (2FLC). The goal of this approach is to better understand the individual effects from learning-by-doing (LBD) and learning-by-searching (LBS). Equation (3) shows the general representation of a 2FLC. Adding another factor to the model reduces the omitted variable bias and better allocates the learning effects. However, a multi-collinearity problem emerges, as both factors (cumulative experience and knowledge stock) might also influence each other.

Jamasb [35] presents an extended 2FLC. The independent variables in this learning-diffusion model are cumulative R&D spending, cumulative number of patents, and time. The dependent variables are both the unit cost of technology, and the cumulative installed capacity. This model is then used to calculate the LBD and LBS rates of different energy technologies. In some cases, the results obtained were not significant or reasonable, thus the 2FLC was used instead.

The LC might also include additional factors other than the effect of LBD, then it is known as a multifactor LC (MFLC). For example, Söderholm and Sundqvist [27] study the cost reductions of wind power in four European countries by fitting twelve different LC models with multiple factors to the same data-set, and to a curtailed version of the data-set. Gan and Li [36] model the cost of PV module cost as a function of cumulative production, Si-prices, supply and demand imbalance, and the market share of cheaper products. Penisa et al. [37] show a model with two and four factors, which tries to improve the projection accuracy of future prices of Li-ion nickel manganese cobalt oxide battery packs. The factors they consider are the cumulative battery demand, the number of patents, the price of lithium, and the price of cobalt.

An MFLC results from the combination of the LC approach and the Cobb-Douglas production function. By deriving the LC from economic theories, Yu et al. [28] study the cost reduction of PV modules due to LBD, LBS, scale effects, price of silicon, and price of silver. Also, Yao et al. [29] use this approach to determine the LRs for different low-carbon energy technologies: wind turbines, PV modules, as well as geothermal, hydropower and biomass power plants.

$$C = C_o\left(\frac{P}{P_o}\right)^b\left(\frac{K}{K_o}\right)^r \tag{3}$$

in which:

K, K_o is the knowledge stock at different moments in time,

P, P_o is the cumulative production at different moments in time,

C is the cost of one unit after the cumulative production P and with knowledge stock K,

C_o is the cost of one unit after the cumulative production P_o and with knowledge stock K_o r is the learning-by-searching index, and b is the experience index.

2.2.2. Multi-component learning curve

The multi-component LC (MCLC), determines the cost of a technology as the sum of the cost of its components, as shown in Equation (4). One of the advantages of this method is that one can consider the fact that each component learns at a different rate. Ferioli et al. [13] use this principle to propose another model, which separates a technology into a learning and a no-learning component. The later can be attributed to elements that do not experience cost reductions (e.g., cost of materials, management costs or financial costs), and serves as an asymptote as the cost reductions do not occur indefinitely.

Rubin et al. [38] estimate the future costs for pulverized coal power plants and natural gas combined cycle power plant with CO_2 capture systems. They use LRs from literature for each component (e.g. flue gas desulfurization, pulverized coal boilers, oxygen production) to project future costs as a function of CIC. Also, a sensitivity analysis is made to study the effect of variable LRs, as well as the effect of lower financing costs, higher fuel prices, lower component capacity estimates, among others.

van den Broek et al. [39] study the technological learning of power plants with carbon capture and storage. They present several LCs for different performance metrics, including removal efficiency, power plant availability, overall energy loss, and energy requirements for CO_2 capture. Then the LRs are used together with projections of capacity growth to determine future cost and performance metrics. Li et al. [40] project the future cost reductions of integrated gasification combined cycle power plants with carbon capture and storage. A LR is estimated for different cost components: unit investment, fixed operational and maintenance costs, fuel costs, cost of electricity, and CO_2 avoidance cost. Then these LR are joint in an MCLC to calculate the LR for the overall energy system.

Knoope et al. [41] study integrated gasification combined cycle power plants and Fischer-Tropsch synthesis plants with and without carbon capture and storage. They account for a pre-learning stage. This means that during the first doublings of the CIC, the costs might increase due to up-scaling uncertainties, deficiencies in reliability and performance, or problems with construction and operation. To validate the results from the LC, they were compared with outcomes from a bottom-up cost model. Nicodemus [42] asses the effect of policies on the technological development of hydrogen production using solar power. The technologies studied are solar PV modules, electrolyzers, concentrated solar power systems and thermochemical reactors. To model the effect of policy support, the growth rate for each technology is used as a proxy. They assume that more policy support would result in higher technological growth rates.

Detz et al. [43] use MCLCs to project the costs of seven synthetic fuel production routes. The current levelized cost of fuel is calculated and a sensitivity analysis is done to determine the effect on the levelized cost of fuel when different assumptions are made. Current CIC values, and LRs for each component are either estimated or obtained from literature. Then, to project future costs, three scenarios are envisioned. Böhm et al. [44] build an MCLC to analyze technological learning of low maturity technologies. They suggest using the cumulative production of the overall system as the proxy for experience for all the components. They also incorporate the term *learning properties* to model the fact that the same component might have different LRs depending on some distinctive properties. The effects of spillovers are also considered by changing the scope of cumulative production (e.g. cumulative production of the whole system vs. cumulative production of each component).

$$C = \sum_{i=1}^{n} C_{o,n}\left(\frac{P_n}{P_{o,n}}\right)^{b_n} \tag{4}$$

in which:

C is the cost of component n after cumulative production P_n,

C_o is the cost of component n after the cumulative production P,

P_n, P_o, is the cumulative production of component n at different moments in time, and b_n is the experience index of component n.

2.2.3. Other models

Nemet [45] proposes a bottom-up cost model for PV modules. The cost changes are modeled as a function of seven technical factors. He found that changes in plant size, cell efficiency, and the cost of silicon were the main factors contributing to observed cost reductions.

Another approach found in literature is the cybernetic theory, which is developed by Wene [46]. It states that the LR can be predicted if the learning system is modeled as a non-trivial machine. Once the learning system and its environment reach a steady non-equilibrium state, the learning system develops an eigen-behaviour, which is described by the LC. Even if no learning is perceived because the observed data is to scatter and the calculated LC does not have a good fit, this theory states that the system is still internally learning.

Pan and Köhler [47] use a logistic curve to represent the technological change and to project expected cost reductions of wind power in the UK. They conclude that this model is able to describe the cost reductions in the early innovation stages, and that it is a better fit than the OFLC. Likewise, they suggest studying the fitting process of the model to the observed data. Ferioli and van der Zwaan [26] use exponential equations to represent cost reductions and technological growth as functions of time. They argue that joining these two models results in a curve equivalent to an LC. The advantage is that one can get more insights from this new approach as it takes into consideration the role of time, growth rate, and productivity. Rivera-Tinoco et al. [48] determine the LR of solid-oxide fuel cells by combining OFLCs with a bottom-up cost model. This includes capital, energy, labor and materials costs. Also, the effect of automation and economies of scale is considered. The cost and capacity data are divided into three development stages (R&D,

pilot, and early commercial stages), and a specific LR is calculated for each one, as well as for all three stages together.

Trappey et al. [49] study the costs of wind power with a hierarchical linear LC model. This representation models cost reductions at two levels. At level 1, the relationship of CIC with installation costs, and at level 2, the effect that other variables may have on the relationship modeled in level 1. They report a better fit for the hierarchical linear LC model than for the OFLC. Daugaard et al. [50] use the Stanford-B model and an S-curve model to determine the effect of learning and economies of scale in the optimal size of a bio-refinery. The result of this study is a relationship between current costs and estimated LR and the optimal future bio-refinery size.

Grafström and Lindman [51] develop a quantitative framework to model the invention, innovation, and diffusion phases of technological change of wind power in Europe. The framework also considers possible effects that may rise from the interaction of these three stages. A total of ten different model configurations are built, including several explanatory factors: the number of granted national and international patents, knowledge depreciation, number of researchers per capita, annual public R&D spending, feed-in tariffs, global and local CIC, investment cost, steel price and natural gas price. Additionally, some disturbance terms are used to represent the any influences of other non-considered factors.

Elshurafa et al. [52] model cost reduction of balance of the system costs of solar PV. They first use an OFLC. Then, they preset an enhanced model in which the learning parameter is represented as a function of the spot price of poly-silicon, steel index price, oil price, and consumer price index. This makes it is possible to model a variable LR that depends on different economic and market metrics.

Castrejon-Campos et al. [24] propose an integrative LC model, which aims to explain different sources of learning and variables that may affect technological costs. This model starts with defining technological capital cost change as a function of two factors: experience and knowledge stock. The experience term is further defined, and one can decide to model the effect of only global experience, only local experience or a combination of both. Additionally, the knowledge factor is described by a function which accounts for the possible delays between R&D investments and actual knowledge creation and includes both an annual knowledge depreciation and creation rate. This model is able to address the omitted variable bias regarding the high level of aggregation of OFLCs, because the experience parameter is further divided into different factors.

2.3. Modeling innovation and technological change of industrial processes

As shown in the last section, various models have been developed to analyze the cost reductions of energy technologies. The LC has also been used to study technological change of several industrial processes. This section summarizes the models found.

Lieberman [53], determines LRs for 37 chemical products by fitting historical data. The performance parameter used is the average market price of these chemicals. Different experience parameters are tested, including time, cumulative industry output, cumulative industry capacity, annual rate of industry output, average scale of plant and rate of new plant investment. The cumulative industry output and the cumulative investment are the variables that best determine the cost reduction. He also reports that the slope of the LR steepens with higher R&D expenses and capital intensity.

Clair [54] modeled OFLCs for low-density polyethylene, high-density polyethylene, ethylene, polypropylene, polystyrene and polyvinyl chloride. The value added per ton produced is used as performance parameter, and the cumulative world production is the experience parameter. The geographical boundaries were set to Western Europe and USA.

Sinclair et al. [55] calculate OFLCs for 221 specialty chemicals by fitting a OFLC to historical data. The performance parameter is the unit manufacturing costs (labor and equipment costs). The experience parameter is the time between the first batch and the current batch produced, as well as the cumulative output. They report that the observed cost reductions come from the small process improvements that result from R&D efforts.

Crank et al. [56] estimate LCs for polyvinyl chloride, polypropylene, and polyethylene in Germany from 1969 to 2002. As experience parameter, the cumulative production is selected. As performance parameter, the market prices are used as proxy for production costs. To account for the effect of changing oil prices in the price of the polymers, the relative oil prices are added as an additional regression variable. Also, to account for relevant economic events that occur during the years under study (e.g., oil crisis), a dummy variable is added. Simon [57] uses the same methodology to analyze the cost reduction of four bulk polymers including polyvinyl chloride, polyethylene, polypropylene, and polystyrene.

Ramirez and Worrell [58] use an OFLC to analyze technological development in energy efficiency for ammonia and urea production in the US between 1961 and 2001. The specific energy consumption (SEC) is the performance parameter, and the cumulative production is used as experience parameter. The benefit of not using prices as performance parameter is that market price variations have no impact on the analysis. They also consider an asymptote to energy consumption, as the production process has a minimum theoretical energy consumption. The data used corresponds to average technologies and to the best available technology.

Brucker et al. [59] uses OFLCs to analyze the energy efficiency improvements of energy-intensive industries, including pulp and paper industry, as well as steel, cement, and aluminum production. They use the specific energy consumption as performance parameter. To account for reductions in specific energy consumption due to improvements in operation conditions, the cumulative annual production is selected as the experience parameter instead of the cumulative installed capacity. Data from the best available technology was found in literature and used to fit the model.

Vimmerstedt et al. [60] use an adapted LC model together with a scenario model to study the effect of policy implementation in the biofuel industry. They propose three adaptations to the OFLC. First, to consider an asymptote for the performance parameter, which value corresponds to that of a mature incumbent technology. Second, to account for various technical parameters together with costs, for example: process yield, feedstock throughput capacity, investor risk premium, access to debt financing. Third, to consider how the various technical parameters behave during the multiple development stages.

Karali et al. [61] use the OFLC to analyze the cost developments of energy efficient technologies for the iron and steel sector in the United States. They develop 75 LCs by fitting historical data of 43 basic Oxygen furnace production routes, and 32 electric arc furnace production routes. The performance parameter is the cost of retrofitting the existing facilities with the energy efficiency measures. The experience parameter is the cumulative energy savings. The effect of market penetration on the LR is also studied. They found an negative correlation between market penetration level and the average LR. The LC model is then used together with a linear optimization energy systems model to determine a future cost-effective adoption of energy efficiency measures.

Wang et al. [62] use a mediating effect model to generate an environmental MFLC. The effect of LBD, LBS, learning-by-importing, and scale effects on air pollutants intensity in China is represented. The proxies used are cumulative production (for LBD), number of patents (for LBS), and the technology import expenditure (for learning-by-importing). Also, three mediating variables are selected to explain the indirect relationship between technological learning and air pollutants intensity: energy efficiency, energy structure, and industrial structure. Different tests are made to determine which variables are indeed significant, and how they correlate with each other.

A cubic learning model is used to estimate a dynamic LR value for various industrial sub-sectors. It models the change in costs as a function of cumulative output and is applied to several case studies [63–68]. All the studies report a variable LR value and better fit for industrial production data when using the cubic model instead of the OFLC.

Faber et al. [69] present a method to use LCs in techno-economic assessments and life cycle analysis to project the economic an environmental performance of emerging technologies. They propose to calculate a composite LR considering the LRs for each system component, as well as factors for process and project contingency and a factor for the indirect cost of the plant. This methodology is then applied to study a carbon capture and utilization system for a cement plant.

3. Literature on accelerating technological change

A first step to accelerate technological change might be to better understand the innovation process. If the factors that may drive or hamper the innovation process are identified, then it may be possible to accelerate and give direction to the transition towards a sustainable energy system [4,5]. Literature offers various methods and hypotheses regarding the optimal conditions and settings to achieve quick innovation, development, and deployment of new technologies. This section summarizes the insights of the selected literature.

Different sources of learning are listed in literature [11,21,23] including learning-by-searching (LBS), learning-by-interacting, learning-by-deployment, which can be further divided into learning-by-doing (LBD), learning-by-using. Also, technological and geographical spillover effects may affect the rate of technological change. Cost reductions may also come from economies-of-scale, automation, market dynamics, and standardization of a product.

Some sources suggest that certain technological characteristics may contribute to increase the development and diffusion rates. Both Wilson et al. [70], and Sweerts et al. [71] propose that small unit size technologies are prone to faster learning rates than large scale technologies. It has also been claimed that the speed of technological change depends on the complexity of the innovation [72–74]. Furthermore, Malhotra et al. [2] developed a topology to categorize technologies and try to explain the source of different learning rates. They differentiate technologies in terms of the degree of customization and their design complexity. Degree of customization refers to the extent to which new technologies need to be adapted to the existing environment. Design complexity is a measure of the number of elements in a technology and the degree to which they interact with each other. Depending on the characteristics of each technology, different policy approaches to drive technological change are recommended.

Other studies assert that innovation characteristics such as relative advantage, perceived appeal, usefulness, and ease of use, as well as compatibility with the existing system, may increase the diffusion rate. Two other characteristics that might drive innovation are trialability and observability. Trialability refers to how easily a technology can be tested before actually purchasing it. The term observability refers to the degree to which the benefits of a new technology are made known. Additionally, the high interdependence on other technologies and the lack of required infrastructure, result in lower diffusion rates [75–77].

Kemp and Volpi [73] study the diffusion of different cleaner manufacturing processes, such as pollution control technologies and waste management techniques. They conclude that considering that the more economically attractive a technology is, the faster it will diffuse is an oversimplification of the complex innovation and learning process. In reality, several endogenous and exogenous mechanisms influence the diffusion of clean technology, including environmental regulation, the market's absorptive capacity, the technology's characteristics, the diffusion of competing technologies, the age of existing physical capital, as well as the costs incurred, and benefits obtained by adopting the new technology.

Moreover, when studying innovation from an economics point of view, one might attribute the slow development and diffusion rates to market failures [78–80]. These are commonly addressed by governmental intervention by means of technology-push and market-pull policies. Technology-push policies are focused on developing new knowledge to improve the design, materials, or production process. This can be done by funding R&D efforts, grants, promoting knowledge exchange, supporting entrepreneurs, and giving opportunities to execute demonstration projects. The market-pull policies aim to create demand and new markets for the new technology. This can be done by means of taxes, subsidies, targets and standards. However, further research is required to set policy measures to effectively drive the innovation process, as improperly designed measures could have the opposite effect [35,81].

Innovation can also be studied from a systems perspective. By analyzing the structure and interactions between the elements of the technology innovation system (TIS), one can understand how the development and deployment process occurs. This approach has been used to study the innovation system of energy technologies [78,82,83] and energy intensive process industries [84]. An extension of the systems approach is developed by Hekkert et al. [5]. This analytical framework focuses on the dynamics of the TIS and lists seven different activities that are present in a well performing system. These activities are also called functions of innovation system (FIS). The FIS are entrepreneurial activities, knowledge development, knowledge diffusion, guidance of the search, market formation, mobilization of resources, and creation of legitimacy. A similar approach was developed by van Alphen et al. [85]. It focuses on studying technology transfer, and lists the following functions: creating adaptive capacity, knowledge diffusion through networks, demand articulation, creation of legitimacy, resource mobilization, market formation, and entrepreneurial activities. Several indicators can be used to map the presence or absence of each function, which gives a more quantitative description of the TIS. For example, to map the function knowledge development, one can look at the number of R&D projects, number of patents, or investments made in R&D. Examples of more indicators to map the development of each function can be found in Ref. [86], and [87].

Bento and Wilson [87] and Bento et al. [88] investigate the factors that determine the duration of the formative phase (FP). This refers to the period in which a new technology emerges/is applied until it is ready to be mass commercialized. The average duration of the PF for energy technologies is 22 years. It was found that new energy technologies which are able to directly substitute an incumbent technology tend to have a relative shorter FP, because available infrastructure, supply capacity and complementary technologies are readily available. On the contrary, energy technologies with a smaller unit-scale do not necessarily have a shorter FP. For example, the observed short duration of PF for large-scale technologies like fluid catalytic cracking (4 years of FP) and jets (7 years of FP) might be a result of stakeholders with low risk aversion, as well as technology-push and market-pull initiatives. The relationship between shorter PF and design complexity, faster up-scaling, technology applications (e.g. end-use, transport technologies) has not been confirmed.

After studying the development and diffusion process of solar PV, Nemet [89] presents a framework that shows how to successfully bring a new energy technology to the market and proposes ways to speed up the process. As part of the framework, three stages are proposed: creating a technology, building a market, and making the technology cheaper. First, new knowledge is created, and scientific understanding is acquired by means of R&D and knowledge spillovers. In the case of PV, this resulted in a better understanding of the photoelectric effect, improved manufacturing processes, as well as new materials, designs and configurations. Second, demand starts to develop by means of niche markets in which the technology can deliver a certain competitive advantage. The fact that PV could have access to multiple high willingness-to-pay niche markets, generated a demand for PV and reduced the need for policies to drive technological change. Furthermore, because of the modular nature of PV, it was easier to satisfy demands at different scales and for different niche markets. Likewise, multiple policies in different countries also helped to create a demand and a stable global market. The last stage focuses on reducing technology costs. Learning-by-doing played an important role, as well as iterative up-scaling. This means that PV producers gradually grew their production processes, while learning and improving at every step. Finally, the fact that solar PV could develop for 50–60 years without facing system integration issues also benefited the observed rate of cost reductions. To accelerate the process of bringing a new technology to the market, Nemet proposes three types of initiatives. First, technology-push strategies, focusing on driving R&D, having a suitable workforce and developing legitimacy by means of public procurement. Second, to drive knowledge distribution by promoting spill-overs, knowledge exchange and access to data, reports and papers. Lastly, to generate demand by focusing on having a robust market and implementing policies that address the possible resistance to change from existing stakeholders.

The following insights were derived regarding how to accelerate the energy transition. First, during the initial innovation stages, it is advised to slowly scale-up the technology, starting with small scale designs and demonstration test. This gives more opportunity to develop experience, and to divide risks and costs into different designs and projects. Second, to manage the amount of public and private investments that go into developing one prototype or demonstration project. This is to avoid hindering the extent to which knowledge can be exchanged between stakeholders, which has also been proven to contribute to learning and knowledge creation. Third, to build legitimization by having an open discussion about the risks and benefits of the technology with the involved stakeholders. This will also help to manage expectations, reduce risk perception, and promote cooperation. Fourth, guidance of the search is the convergence of expectations and vision towards one design or technology. If this selection is done too early in the development process, the system may run the risk of technology lock-in. This might slow down the development of other designs and technologies that might have more learning opportunities and could be more quickly developed. Further research is required to determine the effective timing for a technology to converge in one design and for selecting the technologies that will be further developed. Fifth, while it is true that the industrial transformation needs to be accelerated, the reality is that technological change takes time. Trying to hurry the process might generate multiple issues that were not predicted or might also hinder it. Stakeholders need to have a holistic systemic view to generate an initial plan and iterate form that once some results are obtained.

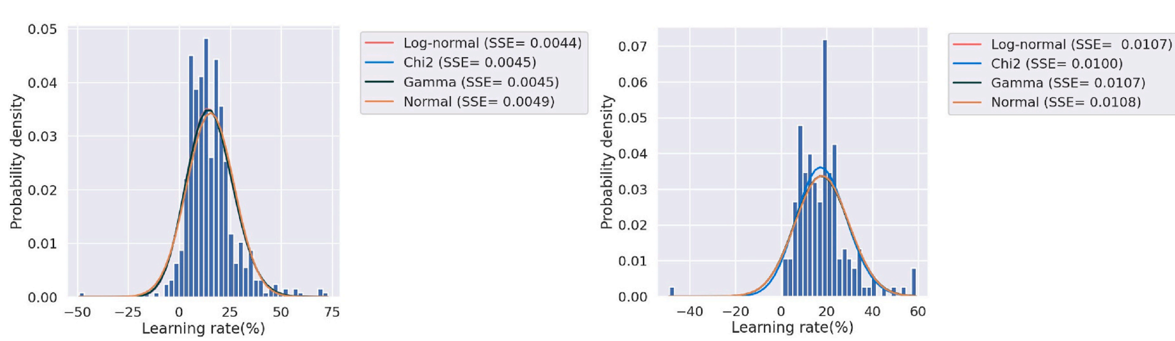
4. Factors determining technological learning rates

As part of the review, a data analysis is performed to provide more insight into the nature of technological change and evaluate the aptitude of OFLCs to represent it. A total of 519 LRs for energy technologies and an additional 226 LRs for industrial processes were gathered from literature. A file with the complete database is included in the Complementary material.

4.1. Energy technologies

To determine which LR is the most probable to find, when studying learning of energy technologies, the 519 found LRs were fitted to different probability distribution functions. This was done by using the *fitter* class form Python's Scipy library. Ten probability distribution functions are fitted to the data (Cauchy, chi squared, exponential, exponential power, gamma, log-normal, normal, power law, Rayleigh, and uniform), and the one with the lowest sum squared error is selected. For the LRs for energy technologies, the probability with the best fit was the log-normal distribution, with a mean $\mu = 15$ % and standard deviation $\sigma = 11$ % (See Fig. 2a). These values differ from the ones reported by Ferioli et al. [13] for 22 different industrial sectors. They found a normal distribution with average $\mu = 19$ %, and standard deviation of $\sigma = 8$ %. Also, the results obtained in this work differ from what is observed in Weiss et al. [15]. They report a normal distribution with $\mu = 18$ % and $\sigma = 9$ % for various energy demand technologies. A possible reason for this discrepancy might be because, in this case, various types of energy technology are considered, including storage, demand, as well as large scale supply technologies like nuclear, coal and natural gas power plants. According to Gallagher et al. [82] the innovation and cost reductions rates in these types of energy technology are slower because of the long lifetime of the capital stock, and the capital intensiveness of large power plants: both of which causes a preference for incremental innovation instead of radical innovation, which has more learning opportunities. Another reason might be the fact that not all the LRs found are statistically significant. If just the values with an $R^2 \geq 0.8$ are considered, the best fit is a chi^2 distribution with a mean LR equal to 18 % and a $\sigma = 11$ % (See Fig. 2b). Likewise, the median of the statistically significant data-set is 18 %, and closely approximates to the values estimated for 26 different LRs for different energy technologies (between 16 and 17 %) [7].

Fig. 3 shows box-plots which depict the distribution of the 519 LRs found. This includes various supply energy technologies, including nuclear, coal, and natural gas power plants, as well as wind turbines (onshore and offshore), biomass power plants, solar PV (which includes modules, cells, inverters, and balance of the system), hydropower plants, solar thermal, marine energy (tidal and wave energy), and geothermal power plants. Demand and storage technologies are included, as well as fuel cells, and H_2 production technologies. The box represents the 25 and 75 percentile and the line in the middle is the median for each energy technology. The median is preferred because it is a summary statistic immune to extreme values. As can be seen, there is variations within and between the LRs of each energy technology.



(a) All data (n=519). Log-normal distribution μ= 15%, and σ= 11%.

(b) Statistically significant data (n=174, $R^2 \geq 0.8$). Chi^2 distribution μ= 18% and a σ= 11%.

Fig. 2. Frequency histogram and fitted distributions of learning rates for energy technologies.

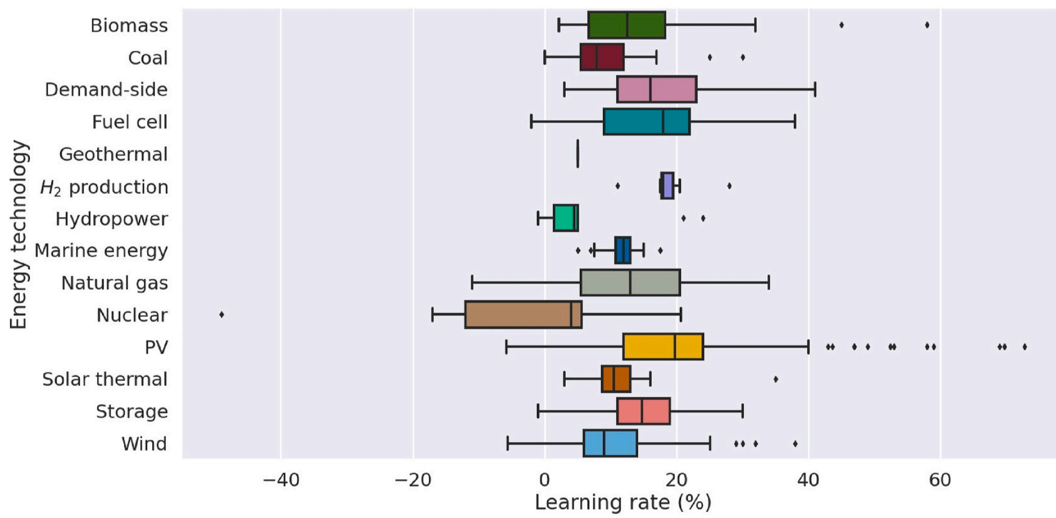


Fig. 3. Box-plots for various energy technologies.

Table 1 shows the summary statistics of the LRs gathered for each energy technology. The numbers inside the parenthesis correspond to the number of data-point gathered for each energy technology. It also reports the mean, standard deviation, the minimum and maximum values, as well as the median. The energy technology with the highest average LR is solar PV (21 %). As previously mentioned, solar PV has experienced significant cost reductions, and is an example frequently studied to get more insight into how to drive cost reduction rates and achieve mass commercialization [89]. The next highest LRs correspond to H_2 production technologies (19 %) and energy demand technologies (18 %). These learning rates might be similar because solar PV and H_2 electrolysis have a similar unit size. Similarly, energy demand technologies are often modular appliances that can be easily produced and sold globally. Doublings in their CIC occur typically more rapidly compared to those of larger technologies, which might be more beneficial for LBD.

The two technologies with the lowest average LR are nuclear (−5%) and geothermal (5 %) power production. In the past nuclear energy has suffered from diminished interest and interruptions in production, which have been known to cause forgetting-by-not-doing (hence the negative LR). Furthermore, Grübler and Wilson [83] estimated the knowledge stock of nuclear energy and report a significant knowledge depreciation due to diminished R&D investment. In the case of geothermal energy, just one LR of 5 % was found. It is not easy to find a cost reduction trend since the costs of this technology depend heavily on the location of the project [29]. The lower LRs for these two energy technologies can also be explained by their intrinsic characteristics (large scale and location dependent).

Technologies that show the most variation in the LR are nuclear, solar PV, and biomass. In the case of nuclear, variability may come from sources not specified by the OFLC, such as stricter safety regulations, lack of available locations to install power plants, and increase in labor costs and commodity prices [18,90]. In the case of solar PV, the variation in LRs might come from the use of different performance metrics, the selection of learning system boundaries, the fact that market prices and not costs are used as proxy for performance or from other factors which cannot be specified by the OFLC (e.g. plant size, module efficiency, and the cost of silicon) [45]. Likewise, the variation the LRs reported for biomass energy might come from the different learning system boundaries, but also from the large variety of feedstocks and technologies available [25].

To test and update empirical insights on technological cost reduction, as well as the ability of the OFLC to depict this process, several hypotheses were formulated following different claims from literature. These hypotheses are then tested using the gathered LRs for energy technologies. First, the LRs were categorized depending on the technology's typical unit size. For example, diodes and other small electronics, were classified in the less than Watt category, while PV modules, refrigerators, microwaves and other demand technologies were categorized in the Watt group. LRs for PV balance of the system and batteries for residential installations, as well as fuel cells, electrolysis systems, and heat pumps were categorized in the kW group. PV power plants, and PV balance of the system for utility scale, as well as onshore wind turbines were allocated in the MW scale. Finally, hydropower plants, natural gas, coal, nuclear and power plants were allocated in the GW magnitude. The results can be seen in Fig. 4. The negative relationship between cost and experience is more noticeable in small-scale technologies than in large-scale ones. This most likely has to do with the ease of learning via iteration that small and modular technologies have [71]. In average both technologies with a scale between < Watt and Watt have a LR between 21 and 23 %, while a mean LR of 16 % and 11 % can be observed for the kW and the MW scales, respectively. Finally, the lowest average LR corresponds to the GW scale, with a mean LR of 8 %. Upscaling nine orders of magnitude (from W to GW) results in a 12 % reduction of the average LR.

Need for customization and design complexity might be factors affecting the LR value. Energy technologies are categorized depending on their need for customization and design complexity (see Fig. 5), as described in Ref. [2]. In this case, the technologies categorized as Type 1 include: fuel cells, electrolyzer cells, PV modules, demand technologies,

Table 1
Summary statistics of learning rates for different energy technologies in percentages.

Energy technology	Mean (%)	Std. deviation (%)	Min/Max (%)	Median (%)
Biomass (32)	15	12	2/58	13
Coal (18)	10	8	0/30	8
Demand-side (82)	17	9	3/41	16
Fuel cell (24)	17	10	−2/38	18
Geothermal (1)	5	–	5	5
H_2 production (9)	19	4	11/28	18
Hydropower (9)	7	9	−1/24	5
Marine energy (23)	12	3	5/18	12
Natural gas (15)	13	11	−11/34	13
Nuclear (6)	−5	25	−49/21	4
PV (153)	21	14	−5/73	20
Solar thermal (8)	13	10	3/35	11
Storage (24)	15	7	−1/30	15
Wind (115)	10	7	−6/38	9

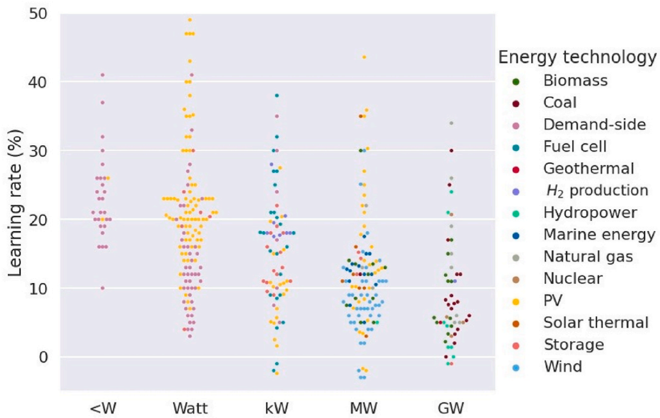


Fig. 4. LRs for energy technologies categorized by their characteristic unit size.

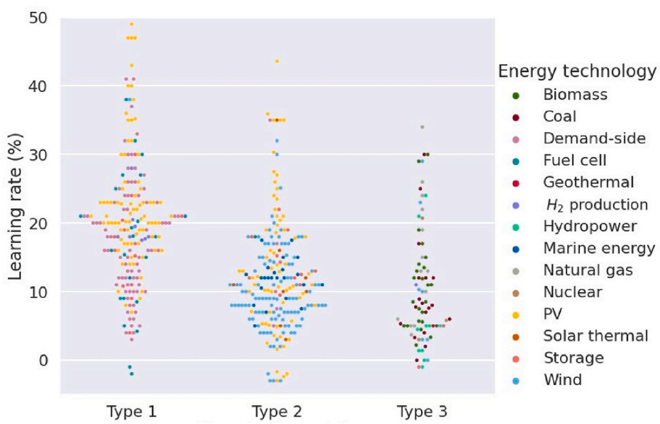


Fig. 5. LRs for energy technologies categorized by their need for customization and design complexity.

and some storage technologies (Li-ion batteries for electronics and electric vehicles and lead-acid batteries), as well as one LR for wind technology (production of submarine high voltage DC cables). An average LR of 21 % is found. On the other hand, Type 2 technologies have an average LR of 12 %. The technologies included in this category are wind turbines, concentrating solar thermal power, tidal and wave energy, PV systems, PV balance of the system, as well as electrolyzer, batteries, heat pumps and fuel cells on a system level. Finally, Type 3 technologies have an average LR of 10 %, and include: coal, nuclear and natural gas power plants as well as biomass power plants, hydropower plants, pumped hydro storage, and offshore wind farms. Type 1 technologies have, in average, a higher LR than the other categories. This agrees with the results presented in Ref. [2] and in Ref. [18]. While this categorization gives indeed a first approximation of an LR for a technology with certain characteristics, the need of customization and design complexity are not the only factors that determine the cost reduction rates. Therefore, not all the data-points are compliant with this assumption, hence the variability found for each category. The standard deviation for Type 1 technologies is 11 %, and for both Type 2 and Type 3 technologies 10 %.

Geographical spillovers may also influence the rate of technological change and learning. Geographical spillovers refer to knowledge and experience generated in one location, which may drive learning and cost reductions in another place. Some studies suggest that all knowledge and experience should be considered as a global good, due to worldwide markets and information exchange [24]. Others propose that changes in hardware costs are mainly subject to global learning, while implementation costs depend more on local learning [91]. To test the effect that geographical location has on the average LR, and the ability of the OFLC to depict geographical spillovers, the LR values were categorized between three different geographical boundaries, depending on what was reported in the original source. Local refers to LRs calculated for a specific country, regional refers to a learning system encompassing several neighboring countries, and global refers to a worldwide learning system. As can be seen in Fig. 6, global LRs are higher than the regional and local ones. The average LRs for the local scope is 15 %, for the regional scope 13 % and for the global scope 20 %. This result agrees with the proposition made in Ref. [91], that promoting local learning may help speed the rate of cost reductions of low-carbon energy technologies. The categorization of the LRs depended on what was reported in the original source, but most of the values were calculated with the global CIC as experience parameter. To have a more realistic representation of the effects of geographical location in technological change, it is important to properly separate the effect of local and global learning.

Literature presents a wide range of perspectives on the influence of the innovation stage on the LR value. Kahouli-Brahmi [11] argues that the LR value will vary at a certain stage of the technology life-cycle, while Junginger et al. [23] state that the LR value tends to reduce as the market starts to saturate, since it might be more difficult to double the CIC. Rivera-Tinoco et al. [48] report LRs for three different development stages of solid-oxide fuel cells. For the R&D stage, a LR of 16 % is reported, and values of 44 % and 12 % correspond to the pilot stage and early commercial stage, respectively. Also, Grübler et al. [76] separate the innovation process into six development stages: invention, innovation, niche market commercialization, pervasive diffusion, saturation, and senescence. They state that it is not possible to model the first two stages with an OFLC. However, if the innovation stage is modeled with a 2FLC an LR of >50 % might be obtained. Ranges between 20 and 40 % are reported for the niche market commercialization, and between 10 and 30 % for the pervasive diffusion stage. Finally, for the saturation, and senescence stages, an LR of 0 % is suggested.

To test if it is possible to allocate a 'typical' LR for each innovation phase, the LRs for solar PV modules were categorized among the four innovation stages: R&D, demonstration, market formation, and commercialization. The LRs gathered are reported for a certain time span, therefore a start and end date are known for each value. The average between the star and end year was calculated. According to this average year and the timeline of the development of solar PV modules presented in Ref. [92], the following time allocation was done. First, from the oldest average year (1974) to 1978, the LRs were categorized as belonging to the R&D phase. Demonstration phase was determined to start in 1979 and end in 1999, while the market formation phase starts from 2000 and ends in 2009. Finally, the commercialization phase starts in 2010 and is still going. Fig. 7 shows how the LR values were allocated. There is just one point in the dataset that corresponds to the R&D phase

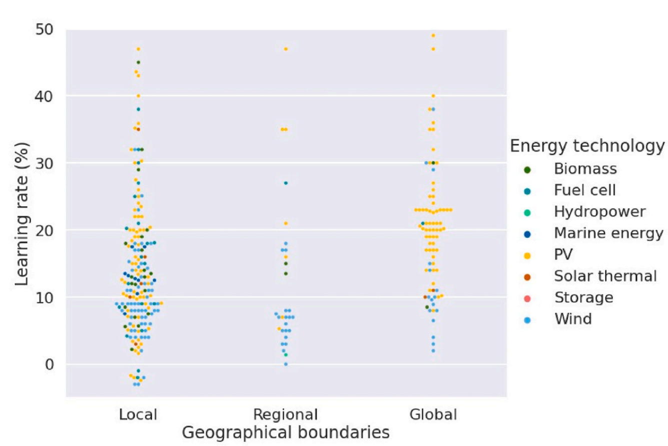


Fig. 6. LRs for energy technologies categorized by geographical location.

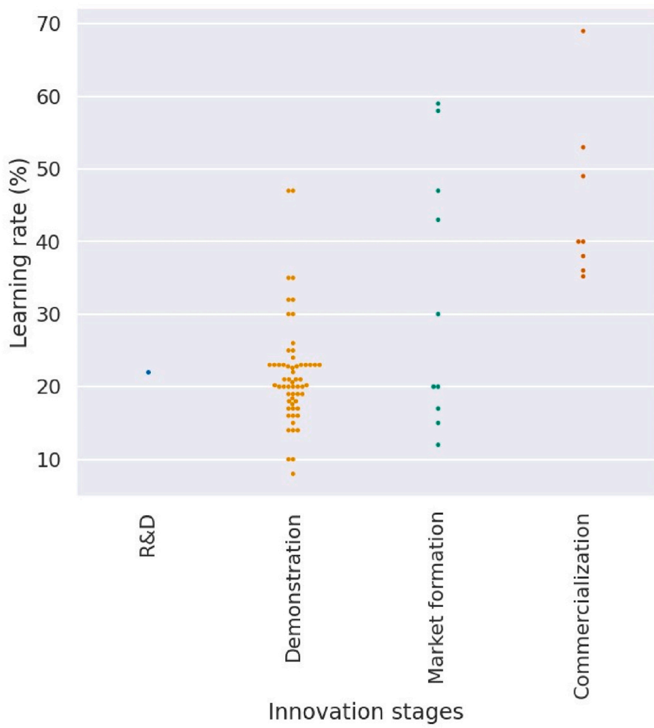


Fig. 7. LRs for solar PV modules allocated to different innovation phases.

and has a value of 22 %. For the demonstration phase, the average LR is 22 %, while for the market formation stage, the mean LR is 32 %. Finally, the mean LR for the commercialization stage is 45 %. No 'typical' LR could be found for a specific innovation stage, however, a trend can be deduced. The average LR for the commercialization phase has the highest value. This might be because the solar PV market is not yet saturated or because during the commercialization stage, the technology benefits form LBD, economies of scale, a growing market size, and the need for new renewable electricity capacity. Also, the legitimacy that has been attained during the last development stages, and the perceived advantage of using PV instead of conventional technologies, may have increased the consumers' acceptance [89].

4.2. Industrial technologies

A review of LRs for the industry resulted in 226 LRs for different industrial sectors. Fig. 8 shows a histogram with the values found as well as the best-fit probability distribution function. The best fit is selected with the *fitter* class in Python. A normal distribution with a mean of 11 %

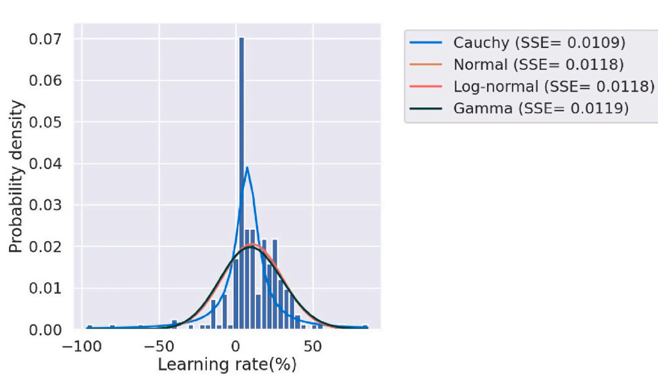


Fig. 8. LRs for industrial processes (n = 226). Normal distribution with $\mu = 11$ % and a $\sigma = 19$ %.

and a standard deviation of 19 % is the one that best fits the data.

Fig. 9 shows the LRs found, which were categorized per industrial sub-sector: food, beverages and tobacco; chemical and petrochemical industry; machinery; paper, pulp and printing; cement and clinker; non-ferrous metals; textile and leather; wood and wood products; non-metallic minerals; iron and steel; transport equipment; and other sectors. The box-plot shows the 25 and 75 percentile and the line in the middle is the median for each industrial sub-sector. Most of the LRs found for industry were calculated for an entire sector and not for a specific technology by collecting historical cost and production data for a specific country and fitting it to an OFLC model.

Table 2 shows the summary statistics found for each sub-sector. As can be seen the sub-sector with largest average LR (25 %) is the one denominated as others. Which includes manufacturing of optical instruments, photographic equipment, transformers and other equipment for power distribution, as well as electronic and electrical equipment. An explanation for these high LRs might be the fact that products are modular, which gives more opportunity to get experience in the production process. Also, the markets are quite dynamic and competitive, therefore, continuous R&D investments are necessary to avoid these technologies to become obsolete. The other sector with a high average LR (23 %) is the manufacturing of trains, cars, trucks and other transportation equipment. This relatively high mean value may be attributed to the large market size and increasing demand. Lastly, the nonmetallic minerals sector has the third largest average LR. This category includes ceramic, clay, glass and brick production. In this case, some of these LRs were calculated with the labor cost as proxy for performance. Therefore, the effect of economic growth and improvements on the country's economic situation might be affecting the LR values.

One of the sub-sectors with the lowest average LR is machinery (1 %) This sector includes the production of electrical, production and general-purpose machinery. Most of these values are calculated for developing countries, in which high-technology industry is not yet well developed. Therefore, small or negative LRs are expected. An average LR of 5 % was found for the iron and steel sector. The LRs reported correspond to brownfield improvements to existing plants. This might be the reason why the values are quite low, as they correspond to incremental innovation, for which not much learning opportunities exist.

In regard to variability, the sectors with the highest standard deviation are the food, beverages and tobacco (37 %) and the machinery (29 %) sectors, as well as the chemical and petrochemical sector (25 %). The source of this variability might come from the different learning system boundaries or from the fact that different technologies are included in the same sector. Other sources of variability still need to be researched.

5. Results

5.1. Barriers and drivers of innovation and technological change

An overview of the drivers and barriers that might accelerate or hinder the invention, development and deployment of new low-carbon technologies, according to the reviewed literature is shown in Fig. 10. These drivers and barriers are organized among different innovation stages: R&D, demonstration, market formation and commercialization. Depending on the technology under study, specific drivers and/or barriers might be dominant in certain stages or might not be present at all. This scheme is an oversimplification of the innovation process. Nevertheless, with this effort we try to bring some light into the complex mechanisms behind technological change of low-carbon technologies. Other barriers and drivers may be identified by carrying out bottom-up engineering analyses, analyzing the innovation system or asking experts.

5.2. Modelling barriers and drivers of innovation and technological change

The second result of these review is presented in Table 3. The 38

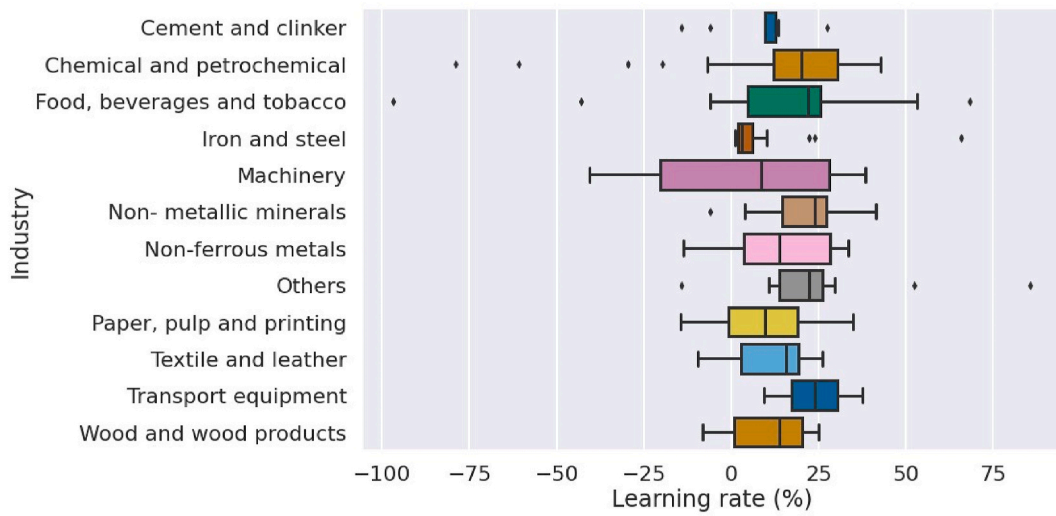


Fig. 9. Box-plots of LRs for various industrial sectors.

Table 2
Summary statistics of learning rates for different industrial sectors in percentages.

Industrial sector	Mean (%)	Std. deviation (%)	Min/Max (%)	Median (%)
Cement and clinker (9)	9	12	−14/27	13
Chemical and petrochemical (41)	15	25	−79/42	20
Food, beverages and tobacco (17)	12	37	−96/68	22
Iron and steel (82)	5	8	1/65	3
Machinery (9)	1	29	−40/38	9
Non- metallic minerals (12)	21	14	−6/41	24
Non-ferrous metals (10)	14	15	−14/33	14
Others (13)	25	24	−14/85	22
Paper, pulp and printing (12)	9	16	−14/35	10
Textile and leather (10)	11	11	−10/26	16
Transport equipment (4)	23	12	9/38	24
Wood and wood products (7)	10	13	−8/25	13

barriers and drivers shown in Fig. 10 are enlisted in the first column. The second column shows the various LC models found in literature that can be used to depict the effect of each barrier/driver. No model found means that this specific barrier/driver could not be found as a parameter in a LC model. The third column enlists other tools, which may help analyze in various degrees and manners, the effect of each driver and barrier.

5.3. *Framework to study technological change for industrial processes*

Many options exist which may contribute to achieving industrial decarbonization. For example, different brownfield improvements can be applied, new low-carbon feedstocks and materials can be used, or new low-carbon technologies can be implemented. However, the costs of these new low-carbon options are generally high compared to the benchmark options. A possible way to speed up industrial decarbonization, might be to identify where the main cost reduction opportunities are, and how to take full advantage of them. It is difficult to generate one specific fit-for-all approach to study technological change of each option in industry. This is because of the various decarbonization options, the variety of processes and technologies in industry, and the numerous factors that might be driving or hindering the speed at which technological change occurs,

Considering the insights obtained in this literature review, we develop a three-level framework aimed at studying learning and technological change of low-carbon industrial processes. Fig. 11 shows a graphical representation of this framework. The *Technology* level refers to a specific technology, for example, an electrolyzers, a gasifier, or a Fischer-Tropsch synthesis reactor. The *Process* level refers to a set of technologies that, together, are used in one chemical plant. For example, biomass goes into a gasifier and syngas is produced. Then, this syngas can be used as feedstock for a Fischer-Tropsch reactor to produce biofuels. The *System* level refers to the political, social, and economic environment that affect the rate of technological change.

The first step is to select the level one wants to study. Depending on the goal, one can choose to focus on a single level, two levels, or on all of them. At the *Technology* level the goal is to identify sources of cost reduction thanks to technological improvements. For example, cost reductions might come from improvements in selectivity, efficiency, catalyst performance, economies of numbers etc. In the *Process* level, the goal is to identify the potential cost reductions when two or more technologies are used together in one industrial process. One might determine which technology in the process has the largest potential of technological improvements and cost reduction. Also, possible cost reductions coming from economies of scale, synergies, heat integration, by-product valorization, etc. might be analyzed. In the *System level*, the goal is to model how financial, political, and social factors might have an effect on the magnitude and rate of potential cost reductions. Investigating all three levels, may give a clearer picture of what is driving or hindering the innovation, development and deployment of new industrial technologies.

The next step is to select the factors one wants to study. As shown in Section 5.1, several factors might be driving or hindering the speed at which technological change occurs. The graphical representation of the framework provides a first guide on how the different factors can be allocated to the three analysis levels. The differentiation of the levels and selection of the factors that are included in the analysis will primarily depend on the judgment of the researcher and the scope and level of detail of the assessment.

Once the analysis level and the (most) relevant factors to study are selected, Table 3 may be used to understand how the effect of these factors has been analyzed before. Studying these examples, might provide guidelines for generating a dedicated model for the case under study, selecting proxies for experience and performance, as well as understanding the level of data requirements and uncertainty that each method entails.

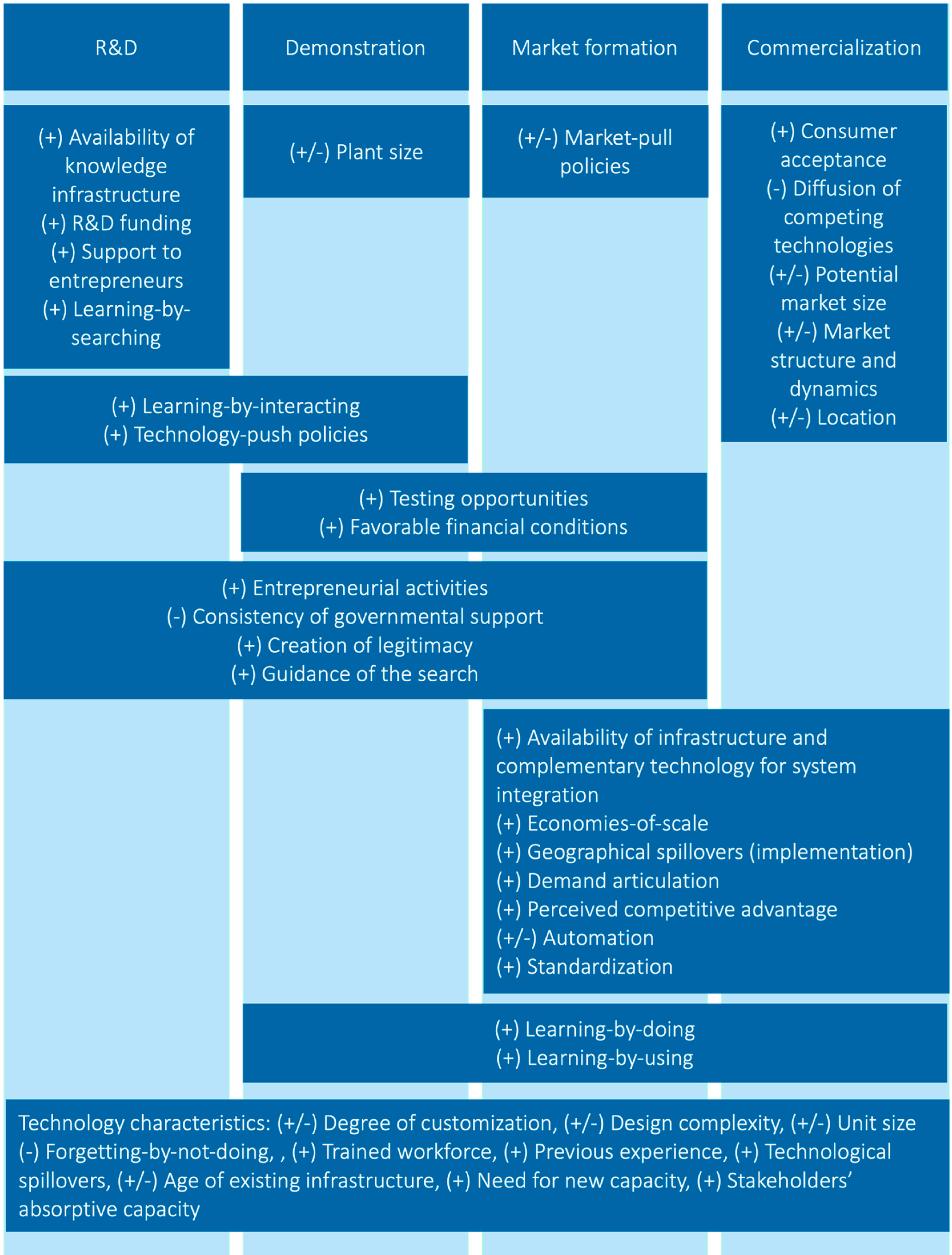


Fig. 10. Drivers (+) and barriers (−) of technological change for different innovation stages.

The next step is to generate a model that projects future costs of the technology/process under study. The methods to generate the model will highly depend on the data availability. Fig. 12 shows the different methods found on the review, and how these can be used in the three-level framework. It also shows a rough approximation of the level of data requirements, level of uncertainty and level of detail that corresponds to each one.

6. Conclusions and recommendations

There is an urgency to accelerate technological change and transform the existing energy and industrial system with the implementation of

Table 3
Methods to model 38 barriers and drivers that may determine technological change of low-carbon technologies. OFLC: one-factor learning curve, MCLC: multi-component learning curve, MFLC: multi-factor learning curve, LR: learning rate, TIS: technological innovation system analysis, FIS: functions of innovation systems analysis. No model found means that a specific barrier/driver has not been used as a parameter in a LC model.

Barriers and drivers	LC model	Other tools
Age of existing infrastructure	No models found	TIS
Automation	De Jong's model	Cost model that accounts for automation effects e.g., Rivera-Tinoco et al. [48]
Availability of infrastructure and complementary technology for system integration	MCLC with an LR for each complementary technology/ infrastructure element e.g., Böhm et al. [44]	TIS
Availability of knowledge infrastructure	No models found	TIS. Expert elicitation
Consistency of governmental support	No models found	Expert elicitation
Consumers acceptance	No models found	TIS
Creation of legitimacy	No models found	FIS
Degree of customization	OFLC	Expert elicitation
Demand articulation	No models found	TIS
Design complexity	OFLC	Expert elicitation
Diffusion of competing technologies	MFLC with market share of competing technologies e.g., Gan and Li [36]	Net present value analysis to determine a portfolio of different energy technologies considering the LR e.g., IEA [6]
Economies-of-scale	MFLC with scale effects e.g., Söderholm and Sundqvist [27] MFLC derived from economic theories e.g., Yu et al. [28]	Cost model that accounts for scale-effects when calculating investment cost or levelized cost e.g., Li et al. [93]; Detz et al. [43]
Entrepreneurial activities	No model found	FIS, TIS
Favorable financial conditions	OFLC with financial indicators as performance parameter e.g., Egli et al. [94]	FIS
Forgetting-by-not-doing	OFLC with negative LR 2FLC considering depreciation of knowledge stock and lags between R&D expenditure and knowledge creation e.g., Söderholm and Sundqvist [27]	Forgetting models e.g. Jaber [34]
Geographical spillovers	New definition of experience which separates the effects of global and local learning e.g., Castrejon-Campos [24] MFLC with both national and international experience e.g., Grafström and Lindman [51]	Mediating model effect with effect of learning by-importing e.g., Wang et al. [62]
Guidance of the search	No model found	FIS, Expert elicitation
Learning-by-doing	OFLC, MCLC, MFLC	Mediating model effect e.g. Wang et al. [62]
Learning-by-interacting	No model found	TIS, FIS
Learning-by-searching	2FLC with cumulative number of patents as proxy for knowledge stock e.g., Mayer et al. [95] MFLC with patent counts as a dependent variable explained by exogenous variables e.g., Grafström and Lindman [51]	Mediating model effect e.g. Wang et al. [62]
Learning-by-using	No model found	TIS
Location	MFLC with effect of capacity factor e.g., Yao et al. [29]	Cost model with localization factor to represent local and foreign plant costs e.g., Li et al. [93] Cost model considering the capacity factor when calculating levelized cost e.g., Detz et al. [43]
Market structure and dynamics	MFLC with input prices as factor e.g., Penisia et al. [37] LR is modeled as a function of different economic metrics e.g., Elshurafa et al. [52] Hierarchical model with variables that may affect the cost reduction e.g., Trappey et al. [49] Add dummy variable to OFLC to account for changing prices e.g., Simon [57]	Sensitivity analysis for changing cost of material e.g., Detz et al. [43]
Market-pull policies	MFLC with feed-in-prices as endogenous variables e.g., Söderholm and Sundqvist [27] Technological growth rare as a proxy for policy support e.g., Nicodemus [42]	Policy intervention studies
Need for new capacity	Model global production as a function of global demand e.g., Gan and Li [36]	Scenarios with different cumulative annual growth rate e.g., Detz et al. [43]
Perceived competitive advantage/ Improved performance	Estimating learning for each cost variable e.g., Li et al. [40] Apply LCs to different plant performance parameters e.g., van den Broek et al. [39]	Cost model to identify technical factors that may reduce costs e.g., Nemet [45] Expert elicitation
Plant size	Stanford-B model and the S-curve model to determine optimal plant size e.g., Daugaard et al. [50]	Cost model to determine how plant size affects costs e.g., Nemet [45]
Potential market size	Model global demand as a function of endogenous variables (e.g., oil prices and feed-in-tariffs) and observed cost reductions e.g., Gan and Li [36]	Diffusion models where cumulative capacity is a function of several variables e.g., Grafström and Lindman [51] Scenario analysis
Previous experience	Stanford-B model	TIS
R&D funding	Stanford-B model 2FLC with effect of cumulative R&D expenditure e.g., Söderholm and Sundqvist [27] MFLC considering domestic public R&D expenditures as endogenous variable e.g., Grafström and Lindman [51]	Expert elicitation
Stakeholders' absorptive capacity	New definition of experience that considers absorptive capacity of knowledge spillovers e.g., Castrejon-Campos et al. [24]	Policy intervention studies
Standardization	No model found	Expert elicitation
Support to entrepreneurs	No model found	Policy intervention studies
Technological spillovers	MCLC which considers the potential spillover effects from competing or parallel technology and component usage and development e.g., Böhm et al. [44] New definition of experience that accounts for spillovers e.g., Castrejon-Campos et al. [24]	Expert elicitation
Technology-push policies	Learning-diffusion model e.g., Jamasb [35]	Policy intervention studies Scenarios

(continued on next page)

Table 3 (*continued*)

Testing opportunities	No model found	TIS
Trained work force	MFLC derived from economic theories, including the cost of labor e.g., Yu et al. [28] MCLC with cost of labor as a cost component e.g., Ferioli et al. [13] MFLC with the number of researchers in the country as endogenous variable e.g., Grafström and Lindman [51]	FIS
Unit size	OFLC	Cost model with scale factor e.g., Detz et al. [43]

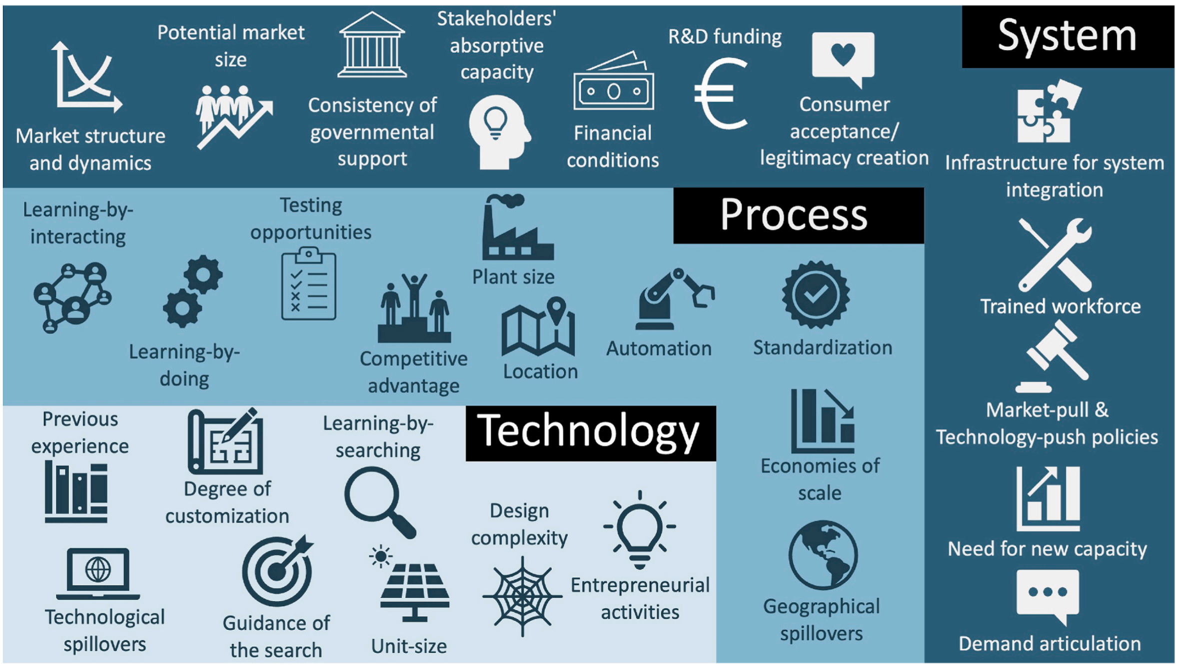


Fig. 11. Framework to study technological learning of low carbon industrial processes.

new technologies, to avoid the worst effects of climate change. Insight into how to achieve a rapid development and deployment of these new technologies may be useful to promote the quick implementation of sustainable industrial processes. The LC tool is an established method used to describe the learning process, typically expressed in terms of cost reductions. The LC approach has mainly been used and adapted to study energy technologies. This has resulted in various new models that attempt to better describe the observed cost reductions. However, the LC method has not been widely used for industrial processes.

The first goal of this work was to give more insight into the factors that may explain the rate of innovation and technological change of low-carbon energy technologies. No less than 38 barriers and drivers of innovation and technological change were found and categorized under different innovation stages: R&D, demonstration, market formation, and commercialization. This classification likely oversimplifies the innovation process. Nevertheless, with this effort we try to shed some light into the complex mechanisms behind technological change and cost reductions of low-carbon technologies. Depending on the technology under consideration, these factors might be dominant in certain innovation stages or might not be present at all. Additional barriers and drivers of cost reductions may be identified by analyzing the TIS, carrying out bottom-up engineering analyses or eliciting experts. Further research is needed to determine the extent to which these factors contribute to cost reductions of industrial processes.

As part of the review, we gathered and analyzed LRs from literature to test existing empirical insights and understanding of the adequacy of OFLCs to represent technological innovation and learning. The following insights were obtained: (1) LRs for energy technologies follow a log-normal distribution with $\mu = 15\ \% \pm 11\ \%$. However, a higher mean LR is found if only the statistically significant data are used. This highlights the necessity for implementing more rigorous reporting standards for LRs, to avoid drawing misleading conclusions. (2) Upscaling the unit size of a technology by nine orders of magnitude results in a 12 % reduction of the average LR. (3) On average, energy technologies with low degree of complexity and low need for customization learn faster. While this categorization gives indeed a first approximation of an LR for a technology with certain characteristics, the unit size, need of customization and design complexity are not the only factors that determine the cost reduction rates. Further research is needed to determine the extent to which other factors also play a role in driving cost reductions. (4) Average global LRs are higher than local ones. To have a more realistic representation of the effects of geographical location in technological change, it is important to properly separate the effect of local and global learning. Further research is necessary to develop methodologies for accurately modeling this effect. (5) No specific LR for each innovation stage could be found. However, a trend can be deduced. LRs at the commercial stage are higher than LRs in the other innovation stages. Additional datapoints are necessary to generate a more robust conclusion. Further research may focus on finding the best method to model learning in the different innovation stages. (6) For industry, most of the LRs that we found do not correspond to a specific technology, but to a whole sub-sector. An average LR was reported for each one, but relatively high variations were found. The literature review revealed an absence of studies addressing the factors influencing learning within these industrial sectors. The results of this review highlight the need to develop deeper knowledge about what is actually driving or hindering the cost reduction rate of industrial processes.

The second goal of this work was to find a set of methods to model innovation and technological change of low-carbon energy technologies

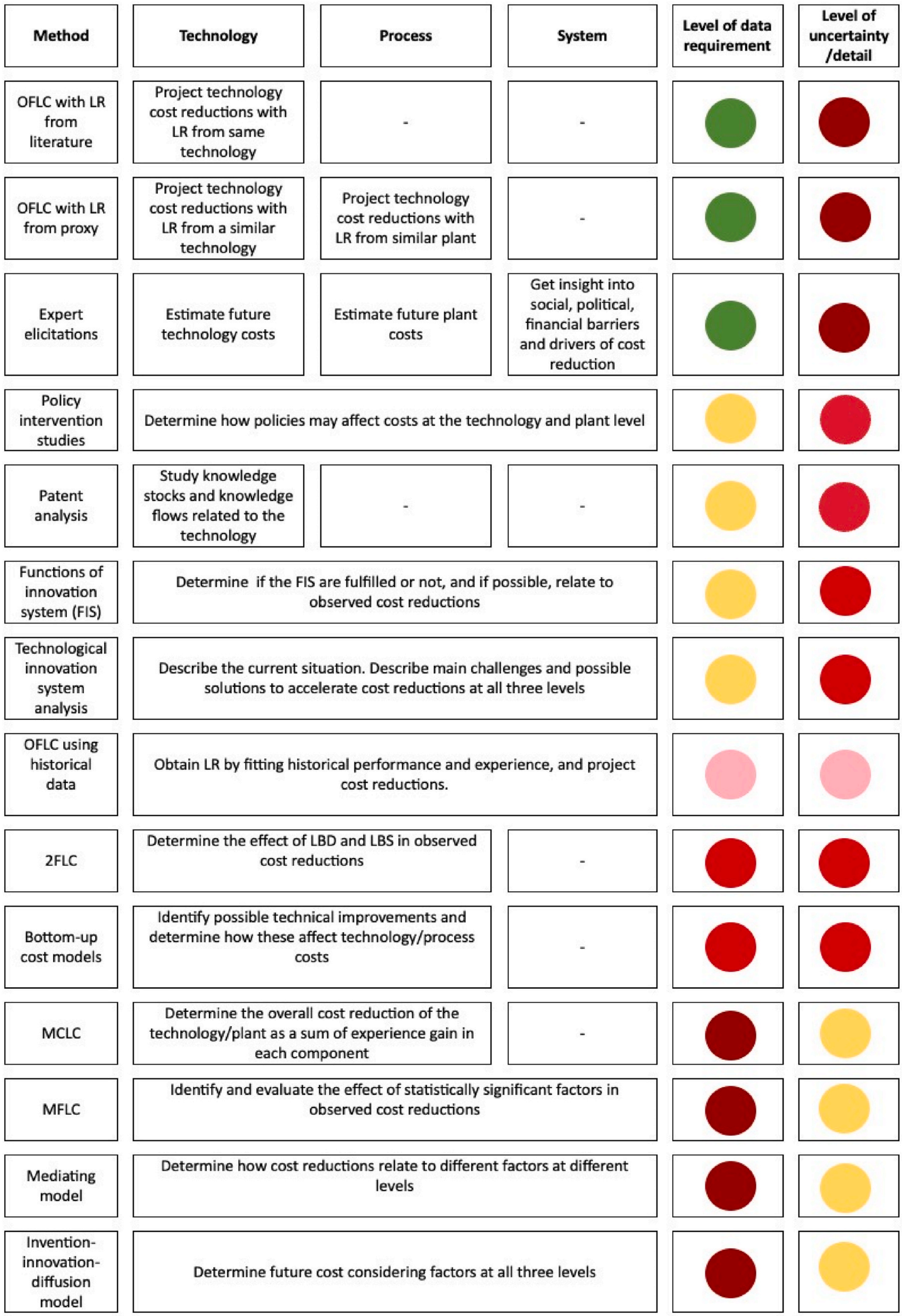


Fig. 12. Overview of methods found in this review, and how these might be applied in the three-level framework to study industrial processes. The level of data requirement and uncertainty are shown in a stoplight format, where dark red means very high and dark green very low. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

and industrial processes. We examine 14 different methodologies for modeling technological change, including patent analysis, FIS, technological innovation systems, and learning curve analysis, among others. LC models for energy technologies are more sophisticated and can determine if the barriers or drivers of technological change are statistically significant to the observed cost reductions. The downside of some of these models is the high data requirements to generate the LC. This may specially be an issue for low-carbon industrial processes for which empirical data might not be available. Most of the models that describe technological change of industrial processes are OFLCs fitted to historical data. Various performance parameters are considered, for example, average market prices, unit manufacturing costs, specific energy consumption, process yield, access to financing, cost of retrofitting existing facilities, or air pollutant intensity. In the case of experience, the proxies explored in literature are cumulative production, cumulative capacity, annual rate of industry output, average scale of the plant, rate of new plant investment, and cumulative energy savings. A suggestion for further research is to test if there are other experience proxies that might be used, and to develop more sophisticated learning models for industrial processes following the framework presented in this work.

The last goal of this work was to develop a framework to study technological change of industrial processes. The three-level approach that we propose can be used to identify if the main cost reduction potential comes from the technology, the process, or system-related factors, and can be applied to the wide portfolio of industrial decarbonization options. Applying the framework might give more insight into the actions to be taken and goals to target to accelerate cost reductions. A suggestion for further research is to apply this framework to various study cases and evaluate its applicability and limitations, as well as to determine how can it be improved. The lessons learned for each case study might be useful to generate rules-of-thumb to model and project future cost reductions of low-carbon processes that might contribute to the transformation of industry.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data used is available as Complementary material

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