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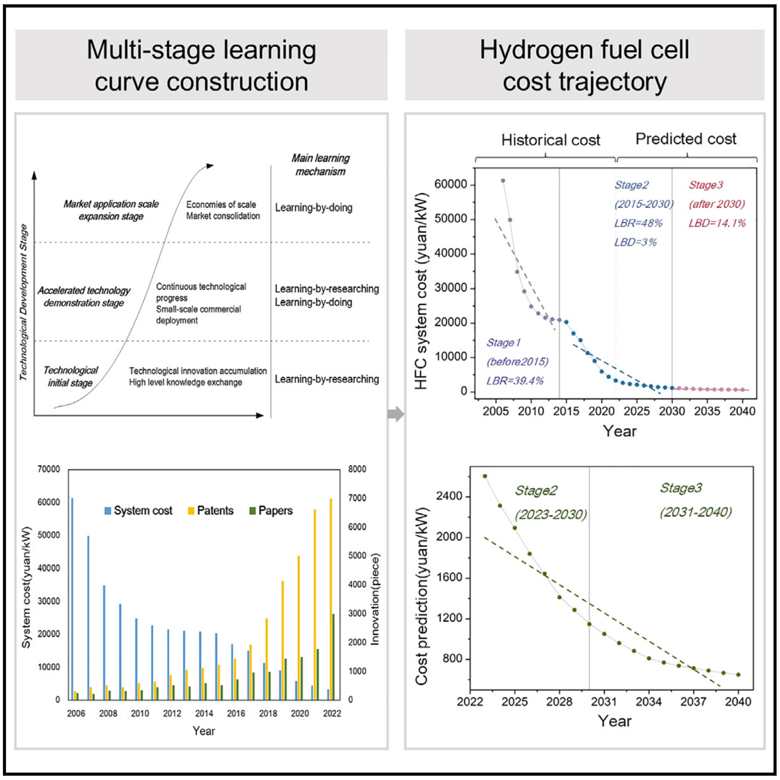
Cost trajectory of hydrogen fuel cell technology in China

Graphical abstract



Highlights

- A multi-stage learning curve model for hydrogen fuel cell technology is constructed
- Both innovation and production significantly reduce hydrogen fuel cell costs
- Innovation drives short-term cost reduction and production dominates long-term
- Hydrogen fuel cell system costs are expected to drop below 1,000 yuan/kW after 2031

Authors

Xue Wang, Li-Wei Fan, Hongyan Zhang, Peng Zhou

Correspondence

hongyan@upc.edu.cn (H.Z.),
pzhou@upc.edu.cn (P.Z.)

In brief

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Cost trajectory of hydrogen fuel cell technology in China

Xue Wang,[1,2] Li-Wei Fan,[1,2] Hongyan Zhang,[1,2,*] and Peng Zhou[1,2,3,*]
[1]School of Economics and Management & Institute of Energy Economics and Policy, China University of Petroleum (East China), Qingdao 266580, China
[2]Institute of Energy Economics and Policy, China University of Petroleum (East China), Qingdao 266580, China
[3]Lead contact
*Correspondence: hongyan@upc.edu.cn (H.Z.), pzhou@upc.edu.cn (P.Z.)
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SUMMARY

Reducing the cost of hydrogen fuel cell technology is crucial in propelling the hydrogen economy and achieving decarbonized energy systems. This study identifies the hydrogen fuel cell cost trajectory through a multi-stage learning curve model, highlighting technology learning mechanisms across different stages. Findings show that innovation and production contribute to cost reduction, and the learning by researching holds a more significant role presently, while the learning by doing takes precedence in the long term, achieving a 14% learning rate. The cost predictions imply that the system cost of hydrogen fuel cell is expected to fall below 1,000 yuan/kW after 2031. Moreover, the scenario analyses highlight the conducive role of various hydrogen production technologies and the evolution of cost influencing factors on cost reduction. Our research provides critical insights into the evolving dynamics of technological learning and cost trajectory in the hydrogen fuel cell industry, with significant implications for policy-making.

INTRODUCTION

Achieving the goal of deep decarbonization in energy systems necessitates the advancement of clean and affordable energy technologies.[1,2] Hydrogen offers a potential solution to the industrial decarbonization dilemma.[3,4] It is pivotal in attaining zero emissions, holding promise as an economically viable clean energy solution for the future.[5] Hydrogen fuel cell can connect the hydrogen energy and electricity market by converting fuel chemical energy into electricity in a clean and efficient manner.[6] Recent years have seen the rapid diffusion of hydrogen fuel cell in transportation, distributed power generation, and energy storage.[7,8] However, the high cost is still one main challenge in prohibiting hydrogen applications. Reducing the cost of fuel cells is crucial for enhancing the viability and sustainability of the hydrogen economy, facilitating the wider adoption of hydrogen within the energy system and accelerating the energy transition.[9,10] The reduction in hydrogen fuel cell technology cost has attracted increasing attention.[11,12]

Understanding the cost dynamics of promising clean energy technologies is essential for accelerating the deep decarbonization process.[13] Different tools have been applied to study hydrogen cost, including levelized cost calculation,[14,15] life cycle cost model,[16] and learning curve model.[17,18] Among these, the learning curve method describes the technology learning mechanisms and enables identifying the key learning source for cost reduction, which helps predict future cost trends. Technology learning is crucial for both cost analysis and advancing technological development.[19] This approach illustrates that the unit cost of the technology tends to decrease as the technology develops and production experience accumulates, which has been widely used in the cost mechanism analysis of energy technology.[20,21] The single-factor learning curve method proposed by Wright[22] is used to measure the cost changes caused by the experience accumulation during the technology development,[23] such as the accumulation of production and technology deployment.[24,25] Two-factor learning curve model further considers the R&D factors, such as R&D investment,[26] knowledge stock,[27] and technological innovation.[28] It distinguishes between learning by doing and learning by researching, which offers a detailed depiction of the technological and cost evolution.[29] The learning by researching (LBR) in learning curve shows that technological innovation will affect the cost, and technology patent is one of the important indicators.[30,31] The increase of technology patent means the accumulation of innovation, which usually promotes the technology advancement and reduces the cost. By quantifying the impact of innovation on costs, it can reasonably predict how costs will fall as technological progress increases.[32] The learning by doing (LBD) suggests that as cumulative production increases, production becomes more efficient, further bringing economies of scale and thus reducing cost. Zheng et al.[33] and Kittner et al.[28] showed that the increase in technology patents and cumulative production could account for the cost reduction of energy technology. Based on these findings, we may conclude that the cost reduction of hydrogen fuel cell, as a rapidly developing energy technology, is influenced by factors such as technological innovation and production scale. Hence, in light of these factors, the learning curve models serve as an effective tool for assessing its cost trajectory.

However, applying these tools to the study of fuel cell cost proves more challenging due to the relatively narrow application areas and limited availability of data. Research has discussed the technical challenges and opportunities of fuel cell in future energy tasks from a cost perspective.[34] Studies have explored the economics and cost trends of hydrogen fuel cell in the main application field of transportation, specifically from the perspective of hydrogen cost.[35,36] Others have discussed total cost of ownership for hydrogen fuel cell vehicles.[37,38] The existing cost analysis of hydrogen fuel cell is mainly from a single perspective of production and focuses on a limited application coverage, and the cost trajectory analysis under multiple dimensions of innovation, production, and policy remains unclear. While these studies reveal the economic potential of hydrogen fuel cell technology, they have not yet fully considered the combined impact of technological development stage and other influencing factors on the cost reduction. Less research has systematically determined the cost path of hydrogen fuel cell. The development of hydrogen fuel cell is a nonlinear process involving multiple factors. It is of practical significance to identify and test the influence mechanisms of the key factors and their effects on cost trend. Therefore, considering the current state of technological development, it is necessary to take the method that covers the technical stages and influencing factors to analyze the cost evolution of hydrogen fuel cell itself.

Governments worldwide have implemented policies and programs to support the development of hydrogen fuel cell technology. Policy supports from the promotion of technological progress,[39] technology application,[40] and infrastructure deployment,[41,42] have promoted technological advancement and cost reduction. Meanwhile, with the growth of market demand, the commercialization of hydrogen fuel cell technology has accelerated significantly worldwide. However, the high cost remains one of the major challenges in the transition to large-scale applications in the global market, making effective cost reduction a critical issue that requires attention. Considering the regional variations in technology development, it is also crucial to understanding cost evolution pattern associated with regional technological factors. As one of the world's leading hydrogen energy producers and markets, China is also currently at an accelerated stage of hydrogen fuel cell technology innovation and application. For instance, according to the International Energy Agency (IEA)'s Global EV Outlook 2023, China has more than 95% of the world's hydrogen fuel cell trucks and nearly 85% of the world's fuel-cell buses. This fact highlights China's pivotal role in driving the adoption of hydrogen fuel cell. Reducing the cost of hydrogen fuel cell in China is not only critical for domestic deployment but also for promoting the global development of the industry. Therefore, identifying the key factors driving global hydrogen fuel cell cost reduction and proposing solutions that integrate regional realities with technological development dynamics, in order to effectively lower global hydrogen fuel cell costs, is an urgent issue that must be addressed.

Based on the aforementioned, we focus on the hydrogen fuel cell technology cost pathways in China. This study aims to propose an improved framework for analyzing hydrogen fuel cell cost trajectory by integrating both regional technology attributes and industrial policies. Specifically, this research focuses on systematically analyzing the diverse cost impact mechanisms of technological innovation and cumulative production across the hydrogen fuel cell development stages. It further examines the contributions of key factors to cost reduction through the application of the learning curve model and explores the future evolutionary path of hydrogen fuel cell cost.

This study generates three potential contributions. First, this paper proposes a multi-stage technological learning framework for analyzing the cost of emerging technologies with limited data. Focusing on hydrogen fuel cell technology, we specifically track the technology learning rates in the initial stage, the accelerated demonstration stage, and the application scale expansion stage, respectively. The staged dynamic cost analyses provide a more accurate reflection of evolving market trends. Second, our work examines the influence mechanisms and structural changes in the cost-driving factors of hydrogen fuel cell technology across different stages, with a focus on separately analyzing the various impacts of innovation and cumulative production on cost reduction. Combining the learning by researching and learning by doing processes, we further develop a multi-stage learning curve model with a bottom-line cost to clarify the evolution of the hydrogen fuel cell cost paths. Third, we integrate both regional technology attributes and industrial policies into our discussion of future cost projections. By considering variations in hydrogen production technology adoption, innovation activities under the demonstration policy effects, and fuel cell application scale, we provide practical insights into regional solutions for accelerating global hydrogen technology learning and cost reduction.

Our findings indicate that with the continuous increase of technological innovation and cumulative production, the system cost of hydrogen fuel cell technology has decreased significantly. The contribution of technological innovation to the cost reduction is greater in accelerated demonstration stage, with an LBR rate of 48%. After 2030, the cost reduction will primarily depend on increased cumulative production, with the LBD rate of 14%. The cost predictions indicate that hydrogen fuel cell system cost in China will be less than 1,000 yuan/kW in 2032, with a slower cost decline rate in subsequent years. In the application scale expansion stage, the adoption of solid oxide electrolytic cell technology will make the cost of hydrogen fuel cell more advantageous, and the increase of fuel cell production will be more favorable to the improvement of cost competitiveness. These findings offer valuable insights for energy decarbonization in fuel cell technology advancements and clean energy industry development forecast.

RESULTS AND DISCUSSION

Calculation of learning rate

In order to analyze the main learning mechanisms and learning rates of hydrogen fuel cell technology in different stages in China (shown in Figure 1), this study describes the development stages and cost analysis strategy of fuel cell technology (see method details). Based on the data of hydrogen fuel cell system cost (from Intelligence Research Group and China Association of Automotive Engineers), the number of patents in China (from IncoPat database) and the cumulative installed capacity in China (from the Ministry of Industry and Information Technology of

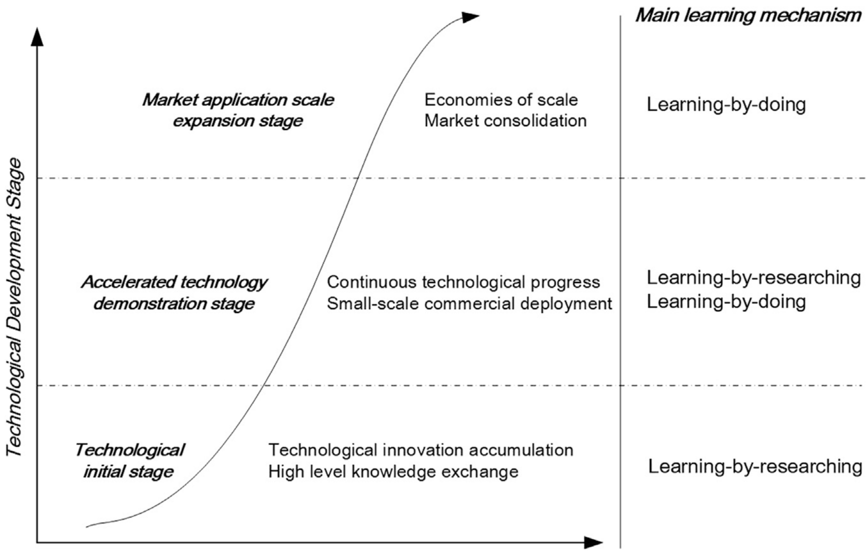

Figure 1. Multi-stage development process of hydrogen fuel cell technology

The figure illustrates three distinct stages of technology development, and each characterized by diverse technology learning mechanisms.

China), we calculated the elasticity coefficients and learning rates in different stages. Specifically, we first adopted one-factor learning curve model for stage 1 and stage 3. According to the estimation shown in Table 1, the learning rate in stage 1 is 39.4%, which means when the technological innovation is doubled, the cost will be reduced by 39.4%. In stage 3, the learning rate is 14.1%, that is, when the cumulative production is doubled, the cost of hydrogen fuel cell system will be reduced by 14.1%. In the two-factor learning curve model adopted for stage 2, the LBR rate and LBD rate are 48% and 3%, respectively. It implies that technological innovation has a greater impact on cost than cumulative production in this stage, resulting in more significant cost reduction. The *p* value of the coefficients are statistically significant for both technology innovation and cumulative production in different stages, with the value of R^2 exceeding 0.56. It indicates that the two factors have significant effects on the cost, and our model has a good fit.

Stage 1: The role of learning by researching (before 2015)

During stage 1, since there are no records of installed capacity before 2015, we can track the cost changes of hydrogen fuel cell technology using the patent applications. The technology evolution of hydrogen fuel cell was primarily driven by technological innovation before 2015. The patents have continued to grow with the support of China's R&D policies and promote technology upgrading and cost reduction. Our calculation of the learning by researching rate can accurately measure the contribution of technological innovation to the reduction of the cost of hydrogen fuel cell technology. The effect of LBR shows that when the number of patents doubles, the cost of hydrogen fuel cell systems will be reduced by 39.4%.

Stage 2: The role of learning by researching and learning by doing (2015–2030)

In the stage 2, we measure the effect of technological innovation and cumulative production on cost changes through LBR rate and LBD rate, with learning rate of 48% and 3% for the two factors, respectively. The learning rates show that when the number of patents is doubled, the cost of hydrogen fuel cell system is reduced by 48%, and when the cumulative installed capacity is doubled, the cost is reduced by 3%. During this period, technological innovation will continue playing a significant role in cost reduction, with cumulative production increasement contributing relatively less to cost in comparison. Notably, China's hydrogen fuel cell production started relatively late and the commercial applications is still not yet mature, and there is considerable potential for production improvements that could lead to cost reductions in the future.

Stage 3: The role of learning by doing (after 2030)

In the stage 3, the market scale of the technology continues to expand. Our model mainly considers the role of learning by doing after 2030 since the Chinese government has set a goal of a relatively complete hydrogen energy industrial system by 2030. Hydrogen fuel cell technology has experienced significant growth in terms of installed capacity since 2015. The installed capacity has increased substantially, rising from 0.6 MW in 2015 to 507 MW in 2022. We analyze the contribution of cumulative installed capacity to hydrogen fuel cell system cost reduction, which is measured by the LBD rate. The learning rate showed that hydrogen fuel cell system cost will be reduced by 14.1% due to LBD effects when the cumulative production of hydrogen fuel cells doubles.

The important contribution of technology deployment to cost reduction has been acknowledged in previous studies.[25,41,43] The deployment of hydrogen refueling stations is deemed an indispensable infrastructure for the hydrogen fuel cell technology development in the long term.[36] According to the China Energy Bureau, the number of hydrogen refueling stations in China was only four in 2015 and exceeded 100 in 2020, with a total of 128 stations built, and the number of hydrogen refueling stations has reached as many as 310 in 2022, reflecting a remarkable growth trend.

To avoid statistical bias from omitted variables, we also constructed a three-factor learning curve model incorporating technology innovation, cumulative production and technology deployment in stage 2. We used the number of hydrogen refueling stations (from China Energy Bureau) as a proxy variable for technology deployment.[34] The results of the elasticity coefficients are shown in Table 1 column (5), where we find that the effect of technological innovation on fuel cell system cost is still

Table 1. Results of one-, two-, and three-factor models

	One-factor models		Two-factor model		Three-factor model			
	Stage 1	Stage 3	Stage 2		Stage 2			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Innovation	−0.723*** (0.096)		2.964** (1.070)	−1.076*** (0.030)	−0.717** (0.202)	−0.787** (0.219)	−0.777** (0.217)	−0.815*** (0.057)
Installed capacity		−0.219** (0.066)		−0.036** (0.011)	−0.003 (0.029)	−0.049** (0.016)	−0.049** (0.015)	−0.048** (0.015)
Deployment					−0.143 (0.112)			
Competition						−1.037 (6.932)	−1.449 (7.179)	−0.596 (4.266)
Cons	7.759*** (0.583)	3.271*** (0.357)	−17.631* (8.140)	10.371*** (0.231)	8.191*** (1.240)	8.564*** (1.508)	8.489*** (1.495)	8.762*** (0.360)
F	29.470	10.900	7.680	633.970	476.330	323.610	325.090	323.380
Prob>F	0.000	0.016	0.032	0.000	0.000	0.000	0.000	0.000
R^2	0.890	0.645	0.561	0.996	0.997	0.996	0.996	0.996
$Adj.R^2$	0.875	0.586	0.488	0.994	0.995	0.993	0.993	0.993

The columns (3) and (4) show the regression results of Equation 5 and Equation 6, respectively. The explained variable is the cumulative installed capacity in column (3) and the fuel cell system cost in all other columns. Statistical significance was determined by ordinary least squares (OLS) regression: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$, and standard error of coefficients is displayed in parentheses.

significant, while the effects of cumulative production and technology deployment are insignificant. Meanwhile, we conducted a collinearity test and the variance inflation factor (VIF) of the three-factor learning curve model showed obvious multicollinearity (VIF = 55).

In addition, the intensification of market competition may affect the cost of a certain technology by promoting technological progress, expanding market scale, strengthening learning effect and more.[44–46] To characterize the market competition for hydrogen fuel cell technology, first, we considered the competition of hydrogen fuel cell vehicles with electric vehicles in transportation sector,[47] and we used two metrics. One is the ratio of sales of hydrogen fuel cell vehicles to sales of electric vehicles (battery electric vehicle [BEV] and plug-in hybrid electric vehicle [PHEV]), and the other is the proportion of sales of hydrogen fuel cell vehicles in new energy vehicle sales (fuel cell electric vehicle [FCEV], battery electric vehicle [BEV], and plug-in hybrid electric vehicle [PHEV]). Second, we considered three technologies within the technical route of hydrogen production technology.[48] Considering the current mainstream water electrolysis for hydrogen production, we searched the patents of alkaline (ALK), proton exchange membrane (PEM), and solid oxide electrolysis cell (SOEC) using the keyword strategy (“water electrolysis, “hydrogen production”, “alkaline electrolyzer” for ALK; “proton exchange membrane electrolyzer” for PEM; and “solid oxide electrolytic electrolyzer” for SOEC) and calculated the market concentration using the Herfindahl-Hirschman index based on the patent share.[49,50]

Based on the aforementioned, we further constructed the three-factor learning curve models covering innovation, cumulative production, and competition, and the estimated results are shown in column (6), (7), (8) of Table 1, respectively. We find that the influence of competition factor is insignificant, and the models (6) and (7) have significant multicollinearity with VIF values of 32 and 31. Therefore, the single-factor and two-factor models constructed in this study are more effective in explaining the change in hydrogen fuel cell technology cost compared to the three-factor models.

Cost prediction of hydrogen fuel cell technology

In the context of China’s hydrogen fuel cell technology status, the cost forecast carries a certain uncertainty due to insufficient time series of current cost. Despite the limited historical data, tracking the cost trajectory of hydrogen fuel cell technology system using available data can provide valuable insights into the technology evolution of hydrogen fuel cell. In order to predict the future cost, it is necessary to determine the key parameters such as learning rate, initial cost, bottom-line cost, number of patent applications, and cumulative installed capacity. This study referred to the U.S. Department of Energy (DOE) [51] and set the bottom-line cost of hydrogen fuel cell system in our model at 220 yuan/kW for the cost prediction. Moreover, in order to calculate the comprehensive growth rates of technological innovation and cumulative production, we took an average of the growth rate series.[33] Based on historical data and calculated growth rates, we simulated the values of patents and installed capacity for further costs prediction. We specifically predicted the cost of hydrogen fuel cell system during the period 2023–2040 with both a one-factor model and a two-factor model. The period from 2023 to 2030 corresponds to the stage where both learning by researching and learning by doing play a role, while the period from 2031 to 2040 represents the stage where learning by doing has a predominant impact. Our model incorporates the main learning mechanisms of each stage, adjusting the learning rate by equal steps to achieve a smooth transition between stages.[52] Specifically, the LBD rate gradually increases

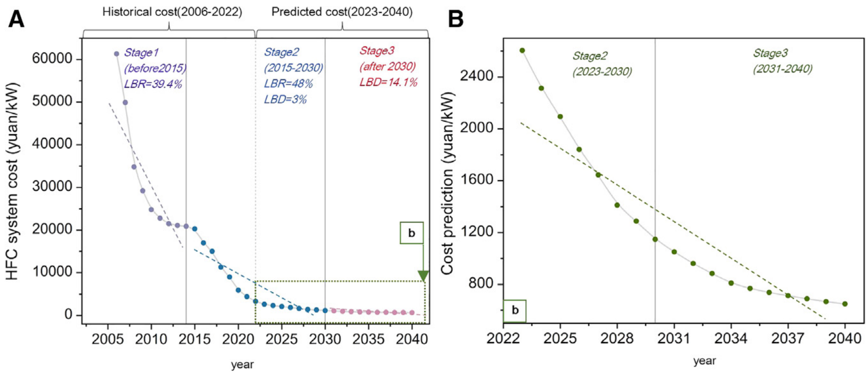

Figure 2. Cost trends of hydrogen fuel cell system

(A) Presents the historical and predicted cost trajectory of hydrogen fuel cell (HFC), and (B) shows the cost projections. Stage divisions mark each phase's end year, and the same below. The LBR and LBD denote learning by researching and learning by doing respectively.

in the last five years of stage 2 and the first five years of stage 3 in equal steps (step = 0.02), with the LBR rate changing inversely relative to LBD rate. Based on annual observations up to 2022, our model analysis depicts the system cost trajectory of hydrogen fuel cell technology across various stages from 2006 to 2040 in Figure 2.

The predictions in Figure 2B show that the cost of hydrogen fuel cell system is expected to decrease to less than 1,000 yuan/kW by 2032. Furthermore, starting from 2038, the predicted cost of hydrogen fuel cell system is projected to drop to less than 700 yuan/kW. We find more significant cost reductions in the late stage 2 compared to stage 3, which attributes greater cost reductions to technological innovation rather than cumulative production. Cost reductions slowdown in the technology stage where learning by doing plays a prominent role, and costs have fallen to relatively low levels. For instance, this paper predicts a system cost of 648 yuan/kW by 2040. Consequently, the cost of hydrogen fuel cell technology is anticipated to become more competitive in the market, facilitating more economical low-carbon development.

Verification of cost prediction

In terms of learning rate estimation, Schwoon's research focused on the LBD process of hydrogen fuel cell technology and predicted the LBD rate of 10%–20%.[53] Therefore, our LBD rate is also within the range of his results, which verifies the reliability of cost prediction to a certain extent. Based on the learning curve model, we used equation 2 and equation 3 in the METHOD DETAILS to predict the system cost of the hydrogen fuel cell. To further verify our predictions, we employed two strategies, including comparisons with actual 2023 cost in China and with results from other hydrogen fuel cell cost analysis studies. First, we compared our forecasted system cost for 2023 with the actual 2023 cost data. Specifically, we calculated the cost based on the LBR rate and LBD rate for stage 2, as well as the predicted values of innovation and production in 2023. We then compared this forecast value with the actual cost in 2023. According to the data of the China Hydrogen Energy Conference, the hydrogen fuel cell system cost in 2023 has been reduced to 2,500 yuan/kW, which is almost consistent with our forecast cost (2,604 yuan/kW) in 2023. Actual cost reduction may be also affected by other unquantifiable factors such as spillover effects from international markets, making our projections slightly higher than actual value. As installed capacity for 2023 is not available and the public patent is not yet comprehensive, the data for 2023 are not included in our historical cost.

Second, this study investigated existing research and reports that predict the cost of hydrogen fuel cell, we compared the cost estimates of hydrogen fuel cell from different researchers and converted the cost units in this study to $/kW. A comparison of projected cost trends for 2023–2040 is illustrated in Figure 3. The differences in the initial values of hydrogen fuel cell cost projections could arise from the varying scopes of research. The studies of Zachmann et al.[17] and Kleen et al.[54] focused on the cost of hydrogen fuel cell stacks in Europe and America, respectively, while the study of UK's Advanced Propulsion Center (APC) focused on the cost of hydrogen fuel cells in light-duty vehicles in UK.[55] Our research focuses on the cost of total hydrogen fuel cell system which covers multiple application scenarios including transportation and distributed power generation, thus leading to higher reported cost values.

Overall, these results show a similar downward trend, and our results are more in line with the Zachmann et al.'s study. The commonality that exists is that we both used a learning curve approach, but his study did not take into account the effect of the LBR. The differences in these cost trends may be caused by diverse research methods. Specifically, the study of Kleen et al. focused on the cost in battery activity loss and performance rather than the systematic cost.[54] The study of APC adopted market research and expert consultation methods, potentially leading to more subjectively optimistic estimations.[55] These two studies did not quantify the impact of the key factors on the cost. Our study aligns more closely with Zachmann et al.[17] which also employs the learning curve approach but only considers the learning by doing mechanism. In our study, in the stage 2 of the hydrogen fuel cell technology development, both technological innovation and cumulative production jointly contribute to cost reduction in our study. Technological innovation has more obvious learning effect for cost reduction. In the stage 3, the technology learning mechanism in our model is consistent with Zachmann et al.,[17] resulting in similar cost trends after 2030.

Compared with other studies, our work has some advantages in using this model to forecast the cost. We consider different learning characteristics and mechanisms at each stage, integrating both learning by researching and learning by doing into cost projections. It reflects the stage progression of technology and closely mirrors the actual development trajectory of

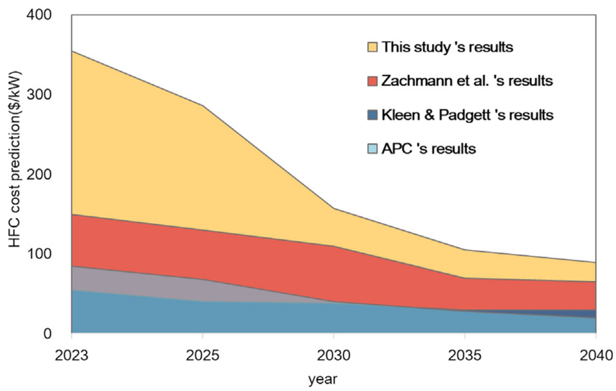

Figure 3. Comparison of the HFC cost prediction from different studies

References and reports cited in the Figure 3:[17,54,55].

The cost projections for hydrogen fuel cell (HFC) from 2023 to 2040 are compared among different studies.

hydrogen fuel cell technology. In the process of cost analysis, we also consider the bottom-line cost, which enhances the rationality of the model. Therefore, the adoption of multi-stage learning curve model is supposed to more realistically reveal fuel cell system cost changes.

Scenario analysis of cost predictions

In order to further clarify the factors affecting the hydrogen fuel cell system cost and their influencing effects, sensitivity analyses of various scenarios, such as different hydrogen production technologies, different technological innovation under policy support, and different technology application scale will be conducted for future cost projections.

(1) Differences in hydrogen production technologies

The hydrogen production technology constitutes the upstream segment of the hydrogen fuel cell technology chain. The choice of hydrogen production technology not only impacts carbon emissions but also determines the cost of hydrogen energy. Changes in the cost of hydrogen fuel cell technology will also be partly influenced by the cost of hydrogen energy source. Fossil fuel hydrogen production and industrial by-production of hydrogen are relatively mature technologies with a lower price at this stage, but it is not conducive for low-carbon and sustainable development. In the context of "dual-carbon" targets, hydrogen production may need to shift from the current dominance of hydrogen production from fossil energy sources to renewable energy sources through electrolysis of water.

According to the difference in electrolyzer types, we focused on the mainstream technologies for hydrogen production from electrolytic water, including ALK, PEM, and SOEC. To be specific, the ALK technology has rich practical experience with relatively lower electrolyzer cost at present, but it requires high power stability and not well applicable to photovoltaic and wind power. PEM and SOEC technology are currently regarded as high potential pathway to green hydrogen but with higher cost. Specifically, PEM electrolyzer is efficient and pressure-resistant with advanced electrode structures but face the challenges of material stability. The SOEC technology operates at high temperatures with cheaper electrodes, but the durability problem needs to be addressed.

To calculate the LBR rates of three technologies, we used data of annual patent number for different hydrogen production technologies based on keyword search strategy in IncoPat database. The common keywords of the three technologies covers "water electrolysis" and "hydrogen production", other keywords include "alkaline electrolyzer" for ALK, "proton exchange membrane electrolyzer" for PEM, and "solid oxide electrolytic electrolyzer" for SOEC. The estimated LBR rates are 44.2% for ALK, 39.0% for PEM, and 35.3% for SOEC in stage 2. Due to the limited data on the China's installed capacity of electrolyzer system, we referred to the studies of Schmidt et al.[56] and Huang et al.[57] and set the learning rate for different technologies. The estimated LBD rates are 18% for ALK, 19% for PEM, and 28% for SOEC technologies, respectively. We also predicted the future cost of the technologies in two stages and show the cost trend in Figure 4.

In stage 2, ALK has a cost advantage over the other two due to its higher LBR rate, and SOEC's higher LBD rate will make it a greater market advantage in stage 3. In addition, PEM will also have more promising cost reduction prospects than ALK in stage 3, and SOEC technology can achieve a lower cost of hydrogen energy supply. Replacing ALK technology in the future with electrolyzer technology that produces hydrogen more efficiently, such as PEM and SOEC, could further promote hydrogen fuel cell technology. The reason for this result is reflected in the various functions of the learning mechanism in different stages. Learning by researching is usually more important in the early stages because new technological innovation can drive greater cost reduction. ALK's increasing innovation in stage 2 will result in incremental cost reductions. In contrast, the large-scale production of PEM and SOEC have not been fully unleashed in stage 2, resulting in higher cost. By stage 3, SOEC's LBD rate has increased significantly, reflecting the gradual release of its production potential, and this accumulation of large-scale production experience has brought significant cost advantages. Combined with the reality of hydrogen production in China, there is relatively more reliance on ALK technology in the early stages of development, and more growth in the application of PEMs and SOECs in the later stages. Due to the relative maturity of the technology, ALK has a notable scale of commercial applications, giving it a cost advantage over the other two technologies in the early stage. Limited by efficiency improvement and low current density operating conditions, the space for cost reduction in the future is relatively limited.[58] PEM excels in flexibility with high current density and fast start-up. However, its reliance on expensive materials such as platinum-based catalysts makes it less advantageous than SOEC technology in the long run.[59] In contrast, SOEC will have a greater advantage in the long term due to its higher energy efficiency potential and scale-up potential, accompanied by technological breakthroughs.[60] Our findings are consistent with Khatiwada et al.,[61] which predicted the convert efficiency from electrical energy to hydrogen energy of different electrolyzer technologies in 2030. The results suggest that SOEC has greater operational efficiency in future hydrogen production development, aligning with the predicted cost reduction trend in our analysis.

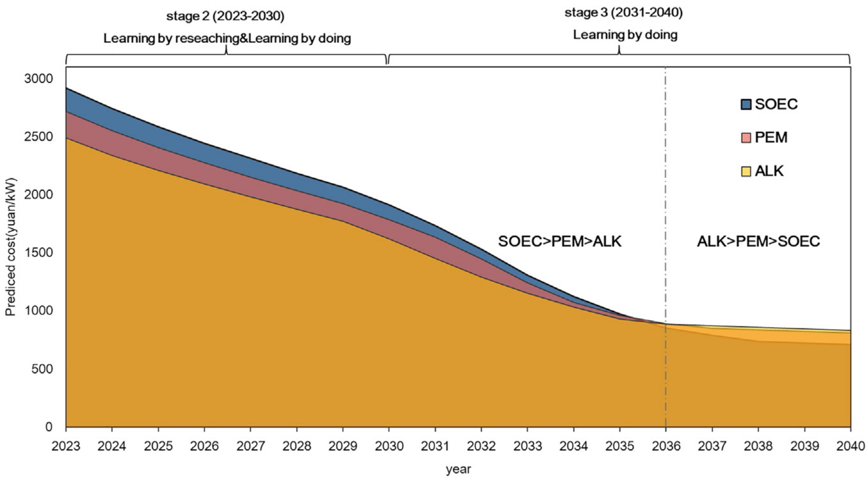

Figure 4. Cost trends under different hydrogen production technologies

The scenario analysis compares three electrolyzer technologies for cost projection. Before 2036, ALK (alkaline) technology holds the advantage, while SOEC (solid oxide electrolysis cell) and PEM (proton exchange membrane) technology become more competitive thereafter.

In order to verify the rationality of the cost prediction of ALK, PEM, and SOEC technologies in our study, this paper made a comparison and analysis of the prediction with the results of existing literatures and related reports in 2030 and 2040, as shown in Figure 5. The figure shows the cost trends of the three technologies in China, and the solid line boxes represent the predicted results of this study. For ALK technology, the results from China Hydropower General Institute were derived from a hydrogen full life cycle production cost model based on historical data. Considering the relative maturity of ALK technology in China, we anticipate a limited growth potential for future ALK production due to its lower efficiency, and therefore the LBD rate is low, which leads to slightly higher cost predictions in our results for 2030. For PEM technology, the results from Reksten et al. were analyzed by a CAPEX model (capital expenditure) that takes operational maintenance costs into account,[62] while we primarily focused on the system cost of the technology, thus our predicted results are relatively low. As for the SOEC technology, the results from Hydrogen and the Future (2021) were presented using a bottom-up approach with cell and stack production lines, and the predictions are highly consistent with our results. On the one hand, these differences in results are due to the varying focus of model assumptions, some studies may emphasize the continuation of historical trends, whereas our model focuses on future innovation and production potential, taking into account the primary driving forces behind these historical trends. On the other hand, differences in data sources, cost structures, and the maturity of technologies at various stages of cost estimation also contribute to the variability across studies. We find that there is little difference in the cost forecast of the long-term development of the technology. Although the methods used are different, the final trend of the cost remains similar. China is currently supporting more short-term scalable ALK and PEM technologies, especially in the early stages of hydrogen energy applications. The support for SOEC is mainly reflected in the medium- and long-term funding, which is also in line with our forecast that SOEC costs are expected to decrease to a lower level in 2040. To sum up, through a comparative analysis of existing studies, the predictions in this paper are consistent with other studies in the major trends, which further confirm the rationality of the forecast in the Chinese context.

(2) Differences in technological innovation under policy support

Some studies suggest that increases in factors such as technological innovation and cumulative production may also be influenced by policy support.[64,65] To promote the application of hydrogen fuel cell technology, China issued the "Notice on the demonstration application of fuel cell vehicles" in September 2020, which formed hydrogen fuel cell demonstration city clusters and had a significant impact on the innovation and production of the technology. The policy approved five demonstration city clusters, including 37 cities, and these cities have actively engaged in the application and promotion of hydrogen fuel cell technology. The policy's promotive effect on technological innovation may further impact the cost of hydrogen fuel cell. To explore the trend of cost changes under the influence of the policy, we first applied the difference-in-difference (DID) model to measure the policy's driving effect on patent growth, and subsequently analyzed cost changes.

Using data from 231 cities in China, we focused on patent information from 2015 to 2022 for empirical analysis by month, and September 2020 was the time for policy implementation. We employed the natural logarithm of patent applications as the dependent variable, with demonstration cities comprising the treatment group and non-demonstration cities serving as the control group. Results shown in Table S1 indicate that the demonstration city cluster policy can significantly promote the growth of hydrogen fuel cell innovation in demonstration cities. The DID estimates indicate that the policy implementation generated about an approximately 16.4% increase in patent applications in demonstration cities relative to control cities. Figures S1 and S2 demonstrate that both the parallel trend test and the placebo test have been successfully passed, further confirming the robustness of the results.

The policy sets a four-year demonstration period for cities involved in the program, with five demonstration city clusters approved by the end of 2021, extending the demonstration period until the end of 2025. Based on the aforementioned, we assume that the policy of this demonstration city cluster could be extended to other cities in China in the future, and we will further analyze the sensitivity of cost to the change of innovation under the influence of policy factor from 2026 to 2040. Assuming that this policy is extended to other cities, we further analyze how the cost will change when technological innovation increases

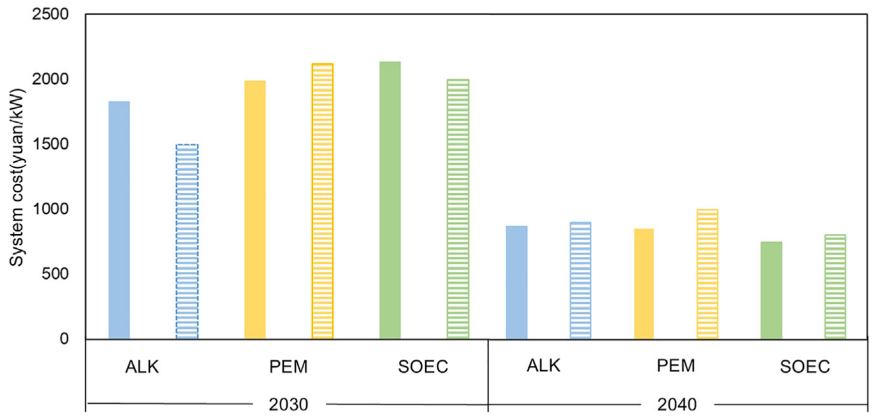

Figure 5. Comparison the of cost prediction for three technologies from different studies

References and reports cited in the Figure 6: China Hydropower General Institute, China Renewable Energy Development Report 2019. PEM technology: [62]. SOEC technology: Hydrogen and the Future (2021), 2021 China's green hydrogen industry status and development prospects http://www.nanoctr.cas.cn/binlab/greetings/202206/P020220621653066445764.pdf).[63] The cost predictions for three electrolyzer technologies (ALK [alkaline], PEM [proton exchange membrane], SOEC [solid oxide electrolysis cell]) are compared between this study (solid boxes) and other studies (dashed boxes).

16.4% in other cities. The basic prediction of cost and the cost trend under stronger demonstration policy support are shown in Figure 6.

We find that with policy support, the cost of hydrogen fuel cell technology declined more compared to the basic prediction. Especially in the stage 2, the cost reduction is more obvious. For example, with policy support, the predicted cost in 2030 is 2.0% lower compared to the basic prediction, and 0.6% lower in 2040. This policy primarily influences stage 2 by significantly driving innovation, which in turn enhances cost reduction. At this stage, the LBR mechanism plays a dominant role, further accelerating cost declines.

(3) The growth differences of technology application scale

The application fields of hydrogen fuel cell technology include transportation, aviation, fixed power generation, and other sectors. Presently, its production is mainly applicated in the transportation field, particularly the hydrogen fuel cell vehicles. As an electric vehicle with zero carbon emission, hydrogen fuel cell vehicle shows promising prospects for development and potential of energy transition. According to the relevant research and forecast of the International Energy Agency (2020), the global electric vehicle ownership in 2019 is approximately 8 million. Under the sustainable development scenario, the global electric vehicle ownership is predicted to reach 80 million in 2025, and it is expected to reach 245 million in 2030. Therefore, we divided the development of hydrogen fuel cell vehicles into three scenarios based on the size of their growth. The cost projections for the basic scenario are based on the LBR rate and LBD rate in the previous section. We assumed that the cumulative production of hydrogen fuel cell technology will increase and decrease by 20% under the optimistic and pessimistic scenarios,[66] and we had re-estimated the learning rate based on the two scenarios. In the stage 2, R&D activities continue to play a more important role both in optimistic scenario (LBR rate: 49.6%, LBD rate: 2.6%) and in pessimistic scenario (LBR rate: 47.8%, LBD rate: 2%), In stage 3, the LBD rate changes similar in the optimistic scenario (15.3%) and pessimistic scenario (12.9%). The predicted future cost situations are illustrated in Figure 7.

First of all, in the optimistic scenario, the increase in cumulative production may lead to the increase of technical production experience and the scale of specialized personnel, which further leads to the improvement of the technology learning rate, thereby resulting in more significant cost reduction. In the two stages, the cost in the optimistic scenario experiences a slower decline. Compared with stage 3, we find that the difference between the optimistic scenario and the basic scenario is more pronounced in the stage 2, which is mainly contributed by the LBR effect in the stage 2. In stage 3, the costs of the three scenarios have a more obvious downward trend, which is due to the accumulation of technological innovation and production in stage 2. In the optimistic scenario, the increase in cumulative production not only enhances the learning rate but also facilitates the formation of economies of scale. As cumulative production continues to rise, the growing production experience leads to improved efficiency, which in turn lowers unit cost. This results in a significant reduction in cost during stage 2, setting a lower cost baseline for stage 3. In stage 3, alongside the expansion of production scale, market demand also stimulates production, further enhancing production capacity and creating a virtuous cycle. Therefore, in the optimistic scenario, the cost reduction benefits persist through Stage 3.

Although changes in cumulative production will bring differences in the learning rates and cost trends in diverse scenarios, it is still the LBR that contributes more in the stage 2. Therefore, the differences in cost trends across the three scenarios highlight the importance of prioritizing technological innovation in the stage 2. For example, in the optimistic scenario, the key role of technological innovation in cost reduction generates cumulative effects, laying a solid foundation for further cost reductions in stage 3. Early technological innovation has a cumulative impact on the long-term cost trajectory. Notably, while continued support in stage 3 remains important, it is even more crucial to seize the policy opportunities in stage 2, as this can lead to more significant results with less effort.

Conclusions

This paper develops a multi-stage learning framework to identify the hydrogen fuel cell cost trajectory. By integrating the regional hydrogen technology and policy attributes, this study reveals the structural changes and different learning mechanisms of fuel cell cost factors across various technological stages. We find that in

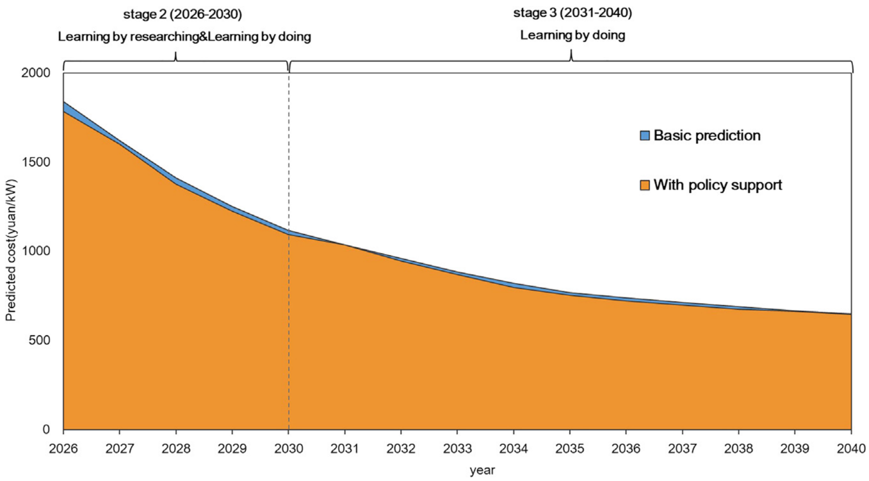

Figure 6. Cost trends of basic prediction and with policy support

The cost predictions are compared between the policy support scenario and the basic scenario.

the early stage of technological development, the cost of hydrogen fuel cell technology system in China has been rapidly reduced depending on learning by researching effects, with a learning rate of 39%. In stage 2, innovation and cumulative production work together to reduce costs, with the LBR and LBD rates being 48% and 3%, respectively. In terms of the cost reduction of hydrogen fuel cell technology system, the learning by researching effect has more obvious advantages than learning by doing, but the joint effect of the two produces a better effect and can reduce costs more quickly in a shorter period. On the basis of the cost reduction to a certain level in the previous stages, the stage 3 aims to achieve a gradual decline in the cost of hydrogen fuel cell through extensive mass production and widespread commercial application, with the learning rate of 14%. This study further clarifies the cost trends based on diverse scenario analyses, and we highlighted the importance of the PEM and SOEC technologies for hydrogen production, as well as the necessity of investment in innovation with stronger policy support and increasing hydrogen fuel cell application scale.

There are several policy implications for development of hydrogen fuel cell and other emerging energy technologies based on our results. First, based on different cost influencing factors and learning mechanisms, the formulation of targeted support policies in technological innovation and production will help achieve cost competitiveness as soon as possible. Second, combined with the staged development of hydrogen fuel cell or other emerging energy technologies, policies should be adapted to the characteristics of technological development at each stage. For emerging energy technologies at an early stage, policies could prioritize increasing R&D investments. For example, policymakers could establish the special R&D subsidy projects or fundings for joint innovation to encourage interregional technology cooperation to facilitate knowledge share and patent innovation activities. At accelerated technology demonstration technological stage, policymakers need to highlight the support both on innovation and market-size, and could put more emphasis on innovation-oriented policies due to higher learning by researching effects in this stage. For example, governments could finance and encourage the large-scale demonstration projects which concurrently foster the emerging energy technologies and accelerate the integration of technology into the market. As the technology matures and economies of scale become apparent, it is more appropriate for providing the scale production incentive to expand the size of market application, building on the foundation established by earlier R&D efforts. At this stage, policymakers can focus on the consumption side

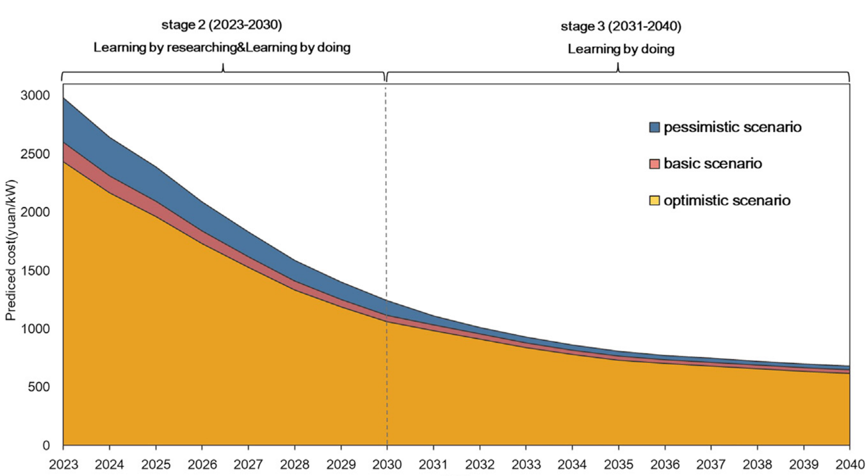

Figure 7. Costs trends under different growth of technology application scales

Three cost prediction scenarios (pessimistic, basic, and optimistic) are compared under different growth of technology application scales.

by adopting consumer purchase subsidies or tax incentives to stimulate market demand and thus expand production. Third, enhancing the cost competitiveness of hydrogen fuel cells requires more than just addressing cost-influencing factors; it also demands a focus on policy support for technologies within the hydrogen value chain. Specifically, during the process of scaling up production, policies can encourage the investment in more promising hydrogen production technologies, such as PEM and SOEC technologies, which is more conducive to reducing hydrogen fuel cell system cost.

Limitations of the study

This study does have limitations and provides some avenues for future research. Firstly, the relatively short history of hydrogen fuel cell technology in China constrained the sample size used for estimating the technology learning. Subsequent research could refine the study by incorporating a more comprehensive dataset. Second, this study identifies the stages of development of the cost of hydrogen fuel cell technology in China, and covering more countries in subsequent study may better account for technology evolution. Third, due to the limitation of data, our cost analysis does not consider the spillover effect of cost reduction in the international hydrogen fuel cell market, and we focus on the case of China that provide some methodology references for other countries or regions. In future research, more factors and more qualitative and quantitative methods could be adopted to explore the developmental patterns of a wider range of hydrogen technologies.

RESOURCE AVAILABILITY

Lead contact

Further information and requests for resources and reagents should be directed to and will be fulfilled by the lead contact, Peng Zhou (pzhou@upc.edu.cn).

Materials availability

This study did not generate new unique reagents.

Data and code availability

- The data used to support this study are listed in the key resources table; the data reported in this paper will be shared by the lead contact upon request.
- This paper does not report the original code.
- Any additional information required to reanalyze the data reported in this paper is available from the lead contact upon request.

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AUTHOR CONTRIBUTIONS

X.W., conceptualization, methodology, data curation, software, formal analysis, visualization, validation, writing-original draft, and writing-reviewing and editing; L.-W.F., conceptualization, methodology, writing-reviewing and editing, supervision, project administration, and funding acquisition; H.Z., conceptualization, methodology, visualization, writing-reviewing and editing, supervision, and funding acquisition; P.Z., conceptualization, methodology, writing-reviewing and editing, supervision, project administration, and funding acquisition.

DECLARATION OF INTERESTS

The authors declare no competing interests.

STAR★METHODS

Detailed methods are provided in the online version of this paper and include the following:

- KEY RESOURCES TABLE
- METHOD DETAILS
  - Stages of hydrogen fuel cell technology
  - The multi-stage learning curve model for hydrogen fuel cell technology
  - Learning rate
  - Variables
- QUANTIFICATION AND STATISTICAL ANALYSIS

SUPPLEMENTAL INFORMATION

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STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Deposited data		
Hydrogen fuel cell system cost in China	Intelligence Research Group, China Association of Automotive Engineers	https://www.chyxx.com/research/nengyuan/ https://www.sae-china.org/
Hydrogen fuel cell patent data	IncoPat database	https://www.incopat.com/
Hydrogen fuel cell installed capacity	Ministry of Industry and Information Technology of China	https://www.miit.gov.cn/
The number of hydrogen refueling stations	China Energy Bureau	https://www.nea.gov.cn/
The policy: Medium and Long Term Plan for the Development of Hydrogen Energy Industry (2021-2035)	National Development and Reform Commission, National Energy Administration	https://www.ndrc.gov.cn/ https://www.nea.gov.cn/
Software and algorithms		
Excel	Microsoft	https://www.microsoft.com/
Stata	Stata	https://www.stata.com/

METHOD DETAILS

Stages of hydrogen fuel cell technology

Technology development typically undergoes a procession from simplicity to complexity and a nascent stage to maturity, exhibiting various characteristics at different stages.[67,68] In the early 2000s, patents for hydrogen fuel cell technology began to increase, and there are no records on installed capacity before 2015 in China. After 2015, the installed capacity of hydrogen fuel cell technology has witnessed significant growth, marking the industry's entry into a new stage of development. At the same time, the Chinese government has introduced policies and strategic plans to support its further advancement. For example, the National Development and Reform Commission of China put forward the following development goals in the Medium and Long-term Development Plan for the Hydrogen energy Industry (2021-2035): By 2030, a relatively complete technological innovation system for the hydrogen energy industry, and an orderly industrial layout will be formed. Therefore, after 2030, hydrogen fuel cell technology may enter a new stage in China. Based on the above content, this study posits that the development of hydrogen fuel cell technology exhibits phased characteristics.

The static technology cost follows a learning curve trajectory,[69] whereas the evolution of hydrogen fuel cell technology unfolds across different technology stages driven by distinct factors and learning mechanisms. Consequently, its technology cost will develop along a dynamic path. The technological innovation of clean energy technology promotes technological progress, leading to the accumulation of learning effect, which is widely observed as "learning by researching".[70,71] The cumulative output and experience generated during the production process also brings learning effects and increases productivity, known as "learning by doing".[21,56] For hydrogen fuel cell in our study, the increase of technological innovation and cumulative production will produce learning effects, which contributes momentum to the reduction of hydrogen fuel cell costs.

The multi-stage learning curve model for hydrogen fuel cell technology

Based on the practical policy development and technology process of hydrogen fuel cell in China, our model will set three stages for technology learning. In the initial stage (before 2015), the development of hydrogen fuel cell technology began with innovative activities, which aimed to demonstrate the performance and feasibility of the technology through research and development activities, as well as knowledge exchange. The reduction of technology cost in this stage is attributed to the mechanism of learning by researching. As technology advances, hydrogen fuel cells are gradually being deployed commercially on a small scale. In the second stage (2015-2030), growing innovation activities are accompanied by a sustained industry expansion through technological promotion and demonstration, and the learning effect of this stage encompasses both learning by researching and learning by doing. In the third stage (after 2030), the technology is expected to reach a relatively mature stage and enters a new phase where the commercial deployment scale in the market continues to increase, resulting in improving scale effects and certain cost competitiveness. Technology research and development decreases with the maturity of technology, and the learning process of cost reduction at this stage is mainly learning by doing.

A learning curve model based on different stages of energy technology can overcome the limitations of the continuity requirements of traditional models.[67] In combination with China's hydrogen fuel cell technology development and data characteristics, this study discusses the background of the hydrogen fuel cell technology development process, and emphasizes the role and changes of different learning mechanisms at distinct stages. Although the learning by doing and researching effects may simultaneously exists in the first and third stage, this study creates a stronger assumption to identify the main driving learning effects in each stage and better understand the whole cost evolution process.

It is worth noting that according to the trend and law of cost development in the previous learning curve function, the technology cost will eventually approach zero. However, the actual technology cost is not infinite. Constructing a learning curve model containing bottom-line cost is more consistent with the real development of technology. Therefore, this study constructed a multi-stage learning curve model of hydrogen fuel cell technology with bottom-line costs.

Therefore, the multi-stage dynamic learning curve is modeled as

$$\text{Stage 1: } C_t = C_0 + (C_1 - C_0) \times IN_t^{-a} \quad \text{(Equation 1)}$$

$$\text{Stage 2: } C_t = C_0 + (C_1 - C_0) \times IN_t^{-a} \times CP_t^{-b} \quad \text{(Equation 2)}$$

$$\text{Stage 3: } C_t = C_0 + (C_1 - C_0) \times CP_t^{-b} \quad \text{(Equation 3)}$$

In the model, C_t represents the system cost of hydrogen fuel cell technology, C_1 represents the initial cost, and C_0 is the bottom-line cost of hydrogen fuel cell technology. IN_t refers to the function of technological innovation over time and CP_t is the function of cumulative production over time. a is the elasticity coefficient of technological innovation to system cost, b is the elasticity coefficient of cumulative production to system cost, and t is the year.

Learning rate

The elasticity coefficients of technological innovation and cumulative production in the learning curve function respond to its relevance through the learning rate (LR).[56] We obtain the elasticity coefficients of technological innovation (a) and cumulative production (b) by the ordinary least squares (OLS) model, and a and b represent the impact of technological innovation and cumulative production on cost, respectively. The learning rate is the percentage of reduction in the system cost of the hydrogen fuel cell technology when the technological innovation or cumulative production is doubled, which can be calculated by the Equation 4.

$$LR_{a(b)} = 1 - 2^{-a(b)} \quad \text{(Equation 4)}$$

A traditional one-factor learning curve can only explain one factor that contributes to cost reduction. Our research model considers different main factors across different stages. We argue that part of the reduction in the cost of hydrogen fuel cell technology is attributable to innovation, which is an important part of its technological learning, and part of it is attributable to cumulative production, through which the model identifies the share of innovation and production that is responsible for cost reduction. However, due to the limited data sample and the similar growth trends of innovation and production, there is a multicollinear problem between technological innovation and cumulative production. To solve this problem, we employ a two-step regression method with the introduction of residual variables,[28,33] and the construction of a two-factor learning curve model follows the rationale:

$$CP_t = \alpha_0 + \alpha_1 IN_t + \eta_t \quad \text{(Equation 5)}$$

We eliminate the correlation by introducing a residual variable, and the new coefficients are calculated in the following steps:

$$C_t = \beta_0 + \beta_1 IN_t + \beta_2 \eta_t + \varepsilon_t \quad \text{(Equation 6)}$$

$$C_t = \beta_0 + \beta_1 IN_t + \beta_2 CP_t - \beta_2\alpha_0 - \beta_2\alpha_1 IN_t + \varepsilon_t \quad \text{(Equation 7)}$$

$$C_t = (\beta_0 - \beta_2\alpha_0) + (\beta_1 - \beta_2\alpha_1) IN_t + \beta_2 CP_t + \varepsilon_t \quad \text{(Equation 8)}$$

$$\gamma_0 = \beta_0 - \beta_2\alpha_0 \quad \text{(Equation 9)}$$

$$\gamma_1 = \beta_1 - \beta_2\alpha_1 \quad \text{(Equation 10)}$$

$$\gamma_2 = \beta_2 \quad \text{(Equation 11)}$$

Thus, the final two-factor model is:

$$C_t = \gamma_0 + \gamma_1 IN_t + \gamma_2 CP_t + \varepsilon_t \quad \text{(Equation 12)}$$

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Variables

To measure the cost *(C)*, this study chose hydrogen fuel cell system cost as the object, which constitutes more than 60% of the total hydrogen fuel cell vehicle cost. It includes the fuel cell stack, air compressor, hydrogen circulation pump, and other components. We collected the system cost data of hydrogen fuel cells, laying the foundation for the subsequent analysis of results. Patents are one of the most important tools and carriers for analyzing technological innovation.[72]

To measure the technological innovation (*IN*), this study used the number of patent applications of hydrogen fuel cell. We used CPC code to search hydrogen fuel cell patents, including invention patents and utility model patents. Relevant codes are Y02E60/50 (fuel cells), H01M8 (fuel cells; manufacture thereof), H01M2250 (fuel cells for particular applications; Specific features of fuel cell system), Y02T90/40 (application of fuel cell technology to transportation). We extracted hydrogen fuel cell patent in China from the IncoPat database, highlighting the impact of China's technological innovation activities on the cost reduction of the country. We also present the distribution of hydrogen fuel cell patents across different regions in China in Figure S3, showing that the eastern region is more active. We finally choose patent data as the innovation variable for the following reasons. On the one hand, patents can directly reflect the commercialization and practicality of technological innovation, and it reflects the degree of technological transformation better than academic papers. On the other hand, patent data has clear classification criteria, which makes it easy to apply and analyze. In addition, some patents realize technological innovation based on the theoretical innovation of academic papers, so it is more common for researcher to choose patents to measure innovation.[73–75] However, academic papers also hold innovative value, so we used keyword search strategy (the keyword "hydrogen fuel cell") to collect hydrogen fuel cell papers in China from China National Knowledge Infrastructure (CNKI) database and Web of Science database, and the country searched in the database is China. We additionally plotted trends in the number of patents and the number of papers versus cost, as shown in Figure S4, and we find that the two show opposite trends. In addition, we included the numbers of papers and patents as innovation variable in the single-factor and two-factor models for robustness analysis, and the results are shown in Table S2. We find that the results of robust analysis are similar to those obtained in Table 1. Compared with the results in Table 1, the coefficient of innovation has increased, but the change is not obvious. The results verify the robustness of the results of single-factor and two-factor models in this study.

As for cumulative production (*CP*), this study measured it using the installed capacity of hydrogen fuel cell technology. For a specific energy technology, cumulative installed capacity is the most commonly employed index which reflects the market size,[76,77] thus enabling us to determine the market development status.[56,78]

In summary, using a multi-stage learning curve model enables us to systematically capture the dynamic impact of innovation and production on cost reduction, especially significant when considering different stages of technology and the shift in policy support. We focus on two key factors: technological innovation (patents) and cumulative production (cumulative installed capacity). Technological innovation reflects the rate of progress through the growth in the number of patents, supporting the long-term decline in technology costs. Similar methods have been used in the study of new energy technologies to capture the long-term impact of technological advances on cost reductions.[28] Cumulative production reflects the accumulation of production experience and the impact of scale effects through cumulative installed capacity, which further promotes the reduction of unit costs. This experience effect has been identified as a key factor in reducing production costs in many learning curve studies.[14] In addition, data from these institutions are widely recognized in the field of new energy technology research, such as the Ministry of Industry and Information Technology of China, the China Energy Administration and more. These data have been used as an analytical basis in research,[79,80] providing an accurate foundation for predicting the future cost evolution of hydrogen fuel cell technology.

QUANTIFICATION AND STATISTICAL ANALYSIS

In STATA 15.0, the original least squares (OLS) regression method was used to analyze the impacts of innovation, installed capacity, deployment, and competition on hydrogen fuel cell system cost, with the results presented in Table 1. The significance levels are denoted as follows: *p<0.1, **p<0.05, ***p<0.01. Additionally, the number of patents and papers was used as a proxy for innovation, and the least squares regression was applied again to analyze the effects of innovation and installed capacity on system cost, with the results shown in Table S2. In the scenario analysis for cost predictions, cost predictions were made based on policy effectiveness. The difference-in-differences (DID) model in STATA 15.0 was used to analyze the impact of demonstration policy on hydrogen fuel cell innovation, with the results presented in Table S1, Figures S1 and S2. The significance levels are denoted as follows: *p<0.1, **p<0.05, ***p<0.01.