

Joule Heated Regenerable Carbon Dioxide Capture Filter for Demand Controlled Ventilation in Indoor Applications

Corresponding Author: Professor Yong Tae Kang

This file contains all reviewer reports in order by version, followed by all author rebuttals in order by version.

Version 0:

Reviewer comments:

Reviewer #1

(Remarks to the Author)

This manuscript demonstrated the Joule-heating carbon capture filter for indoor CO₂ control. The manuscript is well written, and the contribution of this work is clear. Some concerns should be addressed before it is published:

1. In the section "Electro-thermal characteristics of carbon fiber", the authors used a DC power supply to heat the material and observe the correlation between voltage and temperature or power and temperature. However, when the DC power supply is continually working, the temperature might increase without limitation because of Joule heating. How do the experiments control the heating time to obtain the temperature at every voltage? Could you please show the temperature rise curve over heating time? Or does the ambient temperature/airflow rate influence the temperature of the material?
2. The regeneration using Joule heating has attracted considerable interest; several studies have been conducted. The advantage of the material in this paper compared to others using Joule heating regeneration is not shown in the context. Therefore, the author should discuss the advantages of this material in the CO₂ filter than other electrothermal adsorbents.
3. Joule heating in this work may affect the indoor temperature or humidity, as shown in Figure 4f. When heating for desorption, both the temperature and RH increase, indicating that the moisture must be released to the indoor environment, causing the humidification effect. This effect also revealed that the adsorbent captures both water and CO₂ at the sorption stage. Therefore, what's the impact of relative humidity on carbon capture? The record of CO₂ capture capacity is tested under humid conditions? Therefore, you should keep the same humidity condition when conducting a performance comparison between materials and filter sorption/desorption?
4. The results may be different under different humidity conditions? Such as Figures 4c and 4d.
5. Some abbreviations should be explained when you first use them, such as HEPA, RMSE, MAE...

Reviewer #2

(Remarks to the Author)

This manuscript explores a new approach to indoor air quality management by integrating a CO₂ capture filter with a demand-controlled ventilation (DCV) system. The filter is made from amine-functionalized silica coated onto carbon fiber, enabling regeneration via Joule heating. The study spans material synthesis, lab-scale characterization, electrothermal analysis, and system-level simulations, including optimization and deep learning-assisted predictive control. The authors report energy savings of up to ~28% compared to conventional DCV systems and propose strategies to further reduce energy consumption.

The work is ambitious in scope, aiming to connect low-concentration CO₂ capture materials with practical building applications, providing a multi-scale perspective from adsorbent properties to system-level performance.

There are several critical issues that limit the manuscript's current suitability for publication:

1. The CO₂ uptake of the coated filter (1.26 mmol/g) is lower than comparable amine-based sorbents in the literature (2–3 mmol/g). This reduction raises questions about practical performance at building scale.
2. Long-term stability tests are limited to 10–20 cycles. Real HVAC systems operate over months to years, and the manuscript does not address the effects of thermal cycling, humidity, dust, or potential amine leaching.
3. Mechanical robustness is not assessed. Spray-coated silica on carbon fiber may delaminate or degrade under airflow-induced vibration, which is critical for real-world application.
4. The impact of indoor humidity on adsorption/desorption performance is insufficiently addressed, despite water uptake being briefly mentioned.

5. Joule heating is demonstrated only at lab scale (10×10 mm plates). Scaling to real building modules introduces uncertainties in power distribution, safety, and system integration, potentially causing uneven desorption.
6. Energy analysis shows that at high CO₂ targets (1,000 ppm) in summer, the CDCV system consumes 34% more energy than conventional DCV, which challenges the claim of overall energy savings.
7. Proposed optimization strategies (increasing adsorption capacity) are theoretical and lack experimental validation, raising doubts about their feasibility.
8. The deep learning model is trained entirely on simulated data, without validation against real occupancy or CO₂ measurements, limiting confidence in real-world performance.
9. Key parameters (Rocc, Rtarget) are based on simulations, but their uncertainty or sensitivity is not discussed.
10. Occupancy scenarios are limited to 1–4 people, which may not reflect the variability in real building environments, reducing generalizability.
11. No detailed cost analysis is provided. The high cost of carbon fiber and Joule heating infrastructure could offset energy savings.
12. The manuscript mentions “modular scaling,” but no intermediate-scale prototype is demonstrated to support feasibility beyond lab experiments.
13. Some experimental details, such as airflow velocity, pressure drop, and sensor accuracy, are not fully specified.
14. Comparisons with alternative low-energy CO₂ capture strategies (e.g., MOFs, liquid scrubbers) are missing.
15. Terms like “efficient” and “practical” are used without quantitative support; the language could be more precise.
16. The Discussion and Conclusion could include a more critical reflection on limitations and potential barriers to real-world adoption.

Reviewer #3

(Remarks to the Author)

This manuscript reports a novel strategy that integrates a Joule-heating-driven CO₂ capture filter into a DAC-controlled ventilation system. Although the proposed Joule-heating regeneration module and adaptive control scheme show potential for improving energy efficiency, quantitative performance comparison with existing CO₂ capture materials and DAC technologies is lacking, and a comprehensive system-level energy and CO₂ emission assessment is not provided. I therefore recommend that the authors to supplement systematic comparative analyses to further clarify and refine the research innovation before resubmission.

1. Innovation in system optimization is not clearly reflected in the title and abstract, and Fig. 1 offers limited insight into the overall system design and performance advantages.
2. The carbon-fiber-supported polyethyleneimine–silica sorbent does not demonstrate clear innovation at the material level. The authors should assess its performance against state-of-the-art DAC sorbents in terms of CO₂ capture capacity, adsorption/desorption kinetics, regeneration temperature, cycling stability, material cost, and other relevant metrics.
3. Joule-heating-based DAC CO₂ regeneration has already been reported (Advanced Materials, 2025, 37(45): e04542; Joule, 2023, 7(6): 1241–1259; Science Advances, 2025, 11(42): eadv6846). The manuscript does not clarify the performance advantages of the proposed filter over these existing approaches, nor does it provide quantitative comparisons of regeneration energy with industrial methods such as temperature or vacuum swing desorption. In addition, thermophysical properties of the filter, including thermal conductivity and heat capacity, should be reported, and temperature distribution during Joule-heating operation should be provided and cross-validated with thermocouple measurements.
4. When testing filter performance in the custom-built setup, key structural parameters (such as fiber winding number or packing density) are not specified. These parameters directly affect pressure drop, which in turn influences fan power consumption in ventilation systems and overall system energy consumption. Such parameters should be measured and reported in the experimental characterization.
5. Real ventilation air is a multicomponent gas mixture, and polyethyleneimine-based materials are sensible to water molecules. Capture and regeneration performance under varying temperature, humidity, and mixed-gas conditions should therefore be evaluated.
6. It is recommended to justify why indoor–outdoor air enthalpy differences are adopted for quantifying the energy load. Also, due to the electricity-driven regeneration in the CDCV system, a comparison of the operational CO₂ emissions between CDCV and conventional DCV could help highlight the practical implications.
7. The conclusion that desorption energy consumption is minimized at 100 °C is not supported by sufficient quantitative analysis.
8. The Avrami kinetic model is used to describe adsorption/desorption behavior, but experimental data and fitting curves are not provided, making it impossible to assess the validity of the model.
9. Long-term operation may lead to oxidative aging of the filter material, degrading adsorption capacity and electrothermal performance. The reported 10–20 cycles are insufficient to support claims of long-term applicability, and extended cycling tests are required.
10. From an application perspective, the manuscript should explain how the gas released during regeneration is handled.

Version 1:

Reviewer comments:

Reviewer #1

(Remarks to the Author)

The authors have addressed most of my concerns, but some revisions still need to be explained in detail.

Related to Q3: The authors mentioned that the closed system is not a practical ventilation system because it is difficult to accurately track low-concentration CO₂ capture behavior in an open system. Therefore, the authors should note this limitation in the revised manuscript to eliminate ambiguity for practical applications.

In addition, as authors mentioned, the dehumidification effect existed in the practical applications. However, the dehumidification effect may be useful in summer, but in practice, a humidification effect is needed in winter. In this case, I suggest that the authors discuss the practical applications across different seasons, taking into account the varying requirements for CO₂ concentration, temperature, and humidity.

Reviewer #2

(Remarks to the Author)

This manuscript presents an ambitious and interdisciplinary study combining materials development, Joule-heated CO₂ capture, structured filter design, ventilation modeling, and machine-learning-based optimization for indoor air quality control. The proposed CDCV system integrates amine-functionalized silica-coated carbon fiber filters with demand-controlled ventilation and deep learning-assisted operation. The topic is highly relevant to building energy efficiency and indoor environmental quality, and the experimental work at the material and filter scale is generally solid and well executed. However, in its current form, the manuscript does not yet meet the quality and validation level expected for the journal due to a clear gap between experimentally validated components and system-level claims, as well as limited benchmarking and uncertainty analysis.

The major comments and notes are as follows:

1- There is a strong mismatch between robust experimental results and system-level conclusions. The sorbent synthesis, characterization, Joule heating behavior, and lab-scale adsorption-desorption tests are convincing and demonstrate stable, reversible CO₂ capture with fast regeneration. However, the extension to building-scale performance is not experimentally validated. All claims related to energy savings and operational advantages of the CDCV system rely on simulation and optimization rather than HVAC or room-scale experiments, which significantly weakens the system-level conclusions.

2- The energy and techno-economic analyses are conceptually reasonable but rely on simplified assumptions. The model does not capture key HVAC dynamics such as part-load efficiency, transient behavior, or humidity-driven control effects. While energy savings are shown in certain scenarios (notably winter), the system also increases energy demand in summer due to regeneration load. These trade-offs are not fully analyzed, and the sensitivity of results to assumptions is not sufficiently addressed, limiting confidence in the robustness of the reported savings.

3- The machine learning framework lacks sufficient methodological detail and validation. The neural network is trained solely on simulation data, with no real-world validation against occupancy or CO₂ measurements. Key details such as dataset size, generalization ability, and uncertainty quantification are missing. In its current form, the ML model should be viewed as a surrogate model rather than a validated control strategy.

4- The indoor CO₂ system model is based on strong simplifications, including well-mixed air assumptions, deterministic occupancy, and idealized control response. These assumptions may lead to overestimation of control performance and energy savings. Their implications should be more clearly acknowledged and discussed.

5- Benchmarking against state-of-the-art materials and HVAC-integrated CO₂ capture systems is insufficient. The adsorption capacity is moderate compared to leading amine-based and structured sorbent systems, suggesting that the main novelty lies in system integration and regeneration strategy rather than material performance. This distinction should be made clearer.

Reviewer #3

(Remarks to the Author)

The paper is now ready for publication.

Version 2:

Reviewer comments:

Reviewer #2

(Remarks to the Author)

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Responses to reviewers's comments

Reviewer #1 (Remarks to the Author):

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Answer: We appreciate the reviewer's comments in this issue and sincerely thank for the valuable comment. As shown in the electro-thermal characterization results, when DC power is applied, the temperature does not increase indefinitely. After a certain period, Joule heating and heat loss reach a balance, and the system approaches a steady-state temperature. To measure the temperature corresponding to each applied voltage, the DC power supply was turned on and set to the target voltage, while the heating region was monitored using a thermal imaging camera. The temperature was recorded once the fluctuations became negligible and a stable value was observed. Following the reviewer's suggestion, a thermal imaging camera capable of video recording was additionally employed to obtain the temperature rise curve. For the temperature measurement, a single carbon fiber bundle was used and the fiber was cut to a length of 60 mm without any coating, and copper tapes were attached to both ends to serve as electrodes for the voltage application. 30-second thermal video was recorded for each voltage case (4, 5, 6 and 7 V), and representative frames at selected time intervals were captured and the results are incorporated into the main text and the supplementary information. The temperature ramp-up and the transition to the steady-state condition occur within approximately 5 sec, which is negligible compared to the total time required for CO₂ desorption. Variations in ambient temperature conditions or air flow rate were expected to have a negligible effect on the material temperature under the present experimental setup; therefore, these parameters were not investigated separately. We hope that this additional explanation and the newly included data sufficiently address the reviewer's concern.

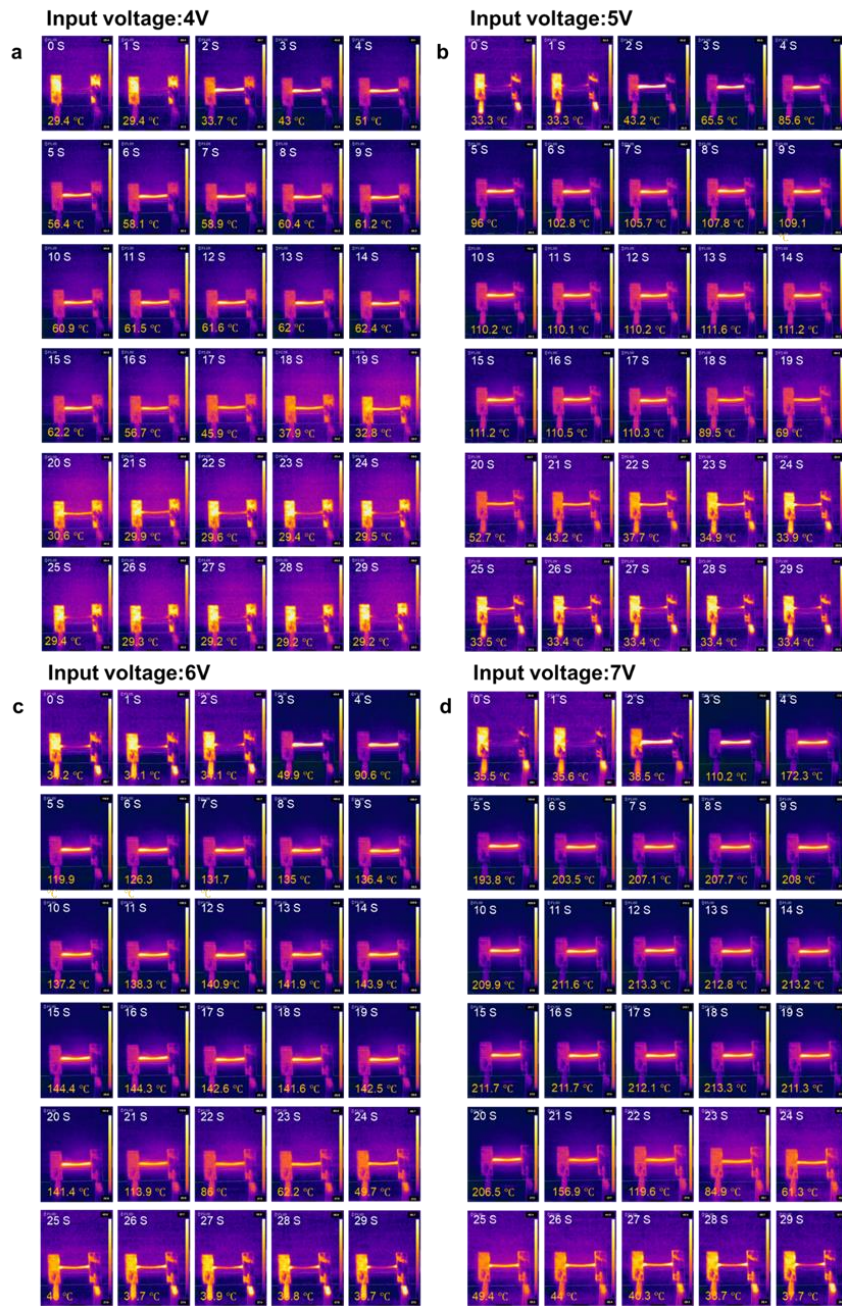
Before:

Supplementary Fig. 9 presents the thermal response of carbon fiber with a single winding over 20 consecutive Joule heating cycles under applied voltages ranging from 4 V to 7 V. The results demonstrate a consistent increase in peak temperature with increasing voltage, while maintaining stable thermal profiles across all cycles. No significant degradation or fluctuation in temperature was observed, indicating that the carbon fiber exhibits excellent thermal

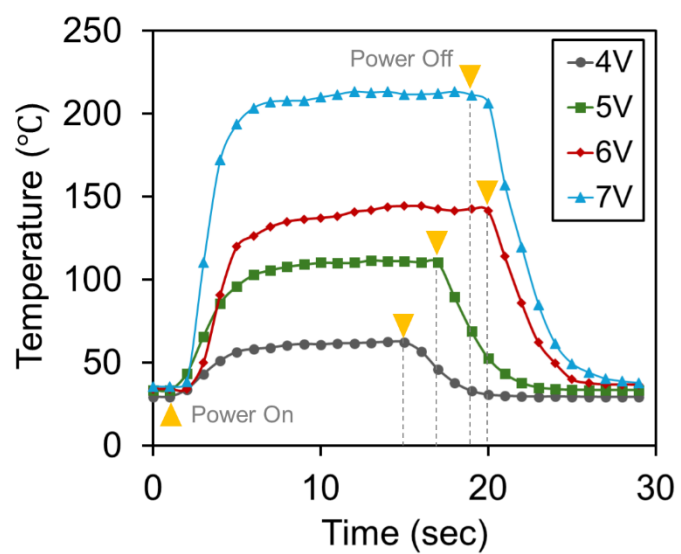
durability and electrical reliability under repeated operation. These findings confirm the material's suitability for cyclic CO₂ desorption processes requiring stable and repeatable heat delivery.

After (Page 10-11):

Supplementary Fig. 9 presents the thermal response of carbon fiber with a single winding over 20 consecutive Joule heating cycles under applied voltages ranging from 4 V to 7 V. The results demonstrate a consistent increase in peak temperature with increasing voltage, while maintaining stable thermal profiles across all cycles. No significant degradation or fluctuation in temperature was observed, indicating that the carbon fiber exhibits excellent thermal durability and electrical reliability under repeated operation. These findings confirm the material's suitability for cyclic CO₂ desorption processes requiring stable and repeatable heat delivery. To further characterize the electro-thermal response of the carbon fiber bundle, time-resolved thermal imaging was conducted under applied voltages from 4V to 7V. Representative thermal images and the corresponding temperature–time curves are provided in the Supplementary Information (Supplementary Fig. 10 and 11). Upon power-on, the temperature rises rapidly and reaches a steady-state within approximately 5 seconds, at which point Joule heating and convective heat dissipation reach thermal equilibrium. Since this stabilization time is negligible relative to the timescale of CO₂ desorption, the electro-thermal response of the carbon fiber is considered sufficiently rapid for the intended application.



Supplementary Fig. 10. Time-sequential thermal images of a carbon fiber bundle under applied voltages of (a) 4, (b) 5, (c) 6, and (d) 7 V.



Supplementary Fig. 11. Temperature–time curves of a carbon fiber bundle under applied voltages of 4, 5, 6, and 7 V.

2. The regeneration using Joule heating has attracted considerable interest; several studies have been conducted. The advantage of the material in this paper compared to others using Joule heating regeneration is not shown in the context. Therefore, the author should discuss the advantages of this material in the CO₂ filter than other electrothermal adsorbents.

Answer: We thank the reviewer for this constructive suggestion. We have added a new Supplementary Table 7 that systematically compares the proposed CO₂ capture filter material with recently reported Joule-heating-based electrothermal adsorbents. The comparison covers sorbent composition, heating element, regeneration method, target application, operating conditions, CO₂ uptake capacity, and cyclic stability.

As summarized in Supplementary Table 7, all prior ETSA studies have targeted either direct air capture (DAC) at 400 ppm or post-combustion flue gas at 5-15 vol% (50,000-150,000 ppm). To our knowledge, the present work is the first to apply Joule-heating-based regeneration to indoor CO₂ management at concentrations of 1,000-2,000 ppm. A detailed comparison with existing ETSA systems, including the three studies cited by Reviewer 3 (Advanced Materials, 2025, 37(45): e04542; Joule, 2023, 7(6): 1241–1259; Science Advances, 2025, 11(42): eadv6846), has been incorporated into manuscript main text and Supplementary Note 8.

The key advantages of the present system relative to prior electrothermal adsorbents are as follows:

(1) The proposed filter achieves vacuum-free regeneration with rapid desorption kinetics, 95% desorption within 15 min at 100 °C and within 35 min at 80 °C under atmospheric pressure. In comparison, Lee et al.¹ required vacuum assistance (0.3 bar) to achieve 95% desorption in 10 min at 110 °C, and Lee et al.² employed a combined e-TVSA process with partial vacuum and a 90-min desorption cycle. The enhanced desorption kinetics observed in the present system can be attributed to the use of nonporous silica nanoparticles as the amine support. Unlike the mesoporous silica (SYLOID C-803) employed by Lee et al.¹, which confines PEI within mesopore channels and introduces significant intra-particle diffusion resistance during CO₂ desorption, the nonporous silica nanopowder (60-70 nm) used in this work positions the amine functional groups predominantly on the external particle surface. This surface-accessible configuration substantially shortens the CO₂ diffusion pathway during thermal desorption, enabling effective regeneration without vacuum-assisted driving force. Furthermore, the thin sorbent layer (14.7-46.1 μm) formed by spray coating ensures intimate thermal contact with the Joule-heated carbon fiber, facilitating rapid and uniform heat transfer to the adsorbent. The elimination of vacuum pumps significantly simplifies the system design and removes the associated noise and energy penalty, which is an essential consideration for deployment in occupied indoor spaces.

(2) The CO₂ uptake capacity of 1.26 mmol g⁻¹ at the filter scale (1.84 mmol g⁻¹ at the powder scale) under 1,000 ppm at 25 °C is comparable to or exceeds those of other fiber-based ETSA systems on a coated-fiber mass basis, such as 0.65 mmol g⁻¹ (Lee et al.¹) and 0.39 mmol g⁻¹ (Lee et al.², Ag-coated fiber basis).

(3) The filter demonstrates superior cyclic stability, retaining full CO₂ capture capacity with a slight increase of 2.28% over 200 adsorption–desorption cycles at 100 °C, which is in stark contrast to the CNF-based system of Wu et al.³ that exhibited 27.6% capacity loss within 40 cycles.

(4) Unlike all cited studies that remain at the material-level demonstration, this work uniquely extends to system-level validation by integrating the CO₂ capture filter with a DCV framework and deep learning-based real-time control, achieving up to 28.3% ventilation energy savings compared to conventional DCV systems.

Supplementary Information

Supplementary Table 7. Comparison of electrothermal CO₂ adsorbents with Joule-heating regeneration

Sorbent	Form factor	Heating element	Regeneration Method	Target Application	T _{ads} (K)	T _{des} (K)	t _{des} (min)	CO ₂ Uptake (mmol g ⁻¹)	Cyclic Stability	Ref
PEI/mesoporous silica	Powder	Carbon fiber	ETSA VSA	+DAC (400 ppm)	30°C	90-110°C	19min (95%, vacuum-assisted)	0.65 (Filter, 400ppm)	10 cycles	¹
EDA-grafted zeolite	Y Powder	Silver nanocomposite	ETSA VSA	+DAC (400 ppm)	25°C	110°C	90min cycle	(desorption) 0.39-0.41 (Fiber, 400ppm)	4 cycles (dry, 5% loss) 10 cycles (humid, 12% loss)	²
PEI/carbon nanofiber	Nonwoven filter	Carbon fiber	ETSA + Solar thermal	Distributed DAC (400 ppm)	25°C	80-105°C	1-2s Joule Heating + ~30min Solar Thermal	1.5 (Filter, 400ppm)	70 cycles (27.6% loss at 40cycles, then stable)	³
Amine-based ion exchange resin/Ag-coated glass flakes	3D-printed monolith	Ag-coated glass flakes	ETSA	DAC (400 ppm)	25°C	70°C	~1 min Joule Heating + ~60 min cycle	1.5 (Monolith, 9vol%, Dry) 0.5 (Monolith, 400ppm, Dry)	10 cycles	⁴
PEI/mesoporous carbon spheres	Spherical particles	Mesoporous carbon spheres	ETSA	Post-combustion (5-15%)	75°C	110°C	30min (ETSA)	3.7 (Powder, 15% CO₂, 75°C, Dry) 4.3 (Powder, 15% CO₂, 75°C, RH 60%)	10 cycles (3% loss)	⁵
SiC-PEI fiber CNT-zeolite fiber	Hollow fiber bundle	SiC or CNT	ETSA VSA	+Post-combustion (15%)	30°C	80-140°C	N/A	0.19 (SiC-PEI, 15% CO₂, Dry) 2.32 (CNT-zeolite, Fiber, 15% CO₂, Dry)	N/A	⁶
Zeolite nanocrystals/carbon foam	Ti-Beta Microcellular carbon foam	Carbon foam	ETSA	Post-combustion (0.15-1bar)	25°C	90-200°C	20min (87%, vacuum-free)	4.6 (Powder, 1bar)	30 cycles (30% loss)	⁷
Zeolite NaUSY/activated carbon	Extruded monolith	Activated carbon	ETSA	Post-combustion (<10% CO ₂)	30°C	100-150°C	N/A	2.23 (Monolith, 20kPa)	N/A	⁸
PEI/nonporous silica	Powder	Carbon fiber	ETSA	Indoor (1000-2000ppm)	25°C	60-100°C	15min (95%, vacuum-free) 35min (95%, vacuum-free)	1.84 (Powder, 1000ppm) 1.26 (Filter, 1000ppm)	200 cycles (2.4% mass loss, no capacity loss)	This Work

PEI : Polyethylenimine

EDA : Ethylenediamine

ETSA : Electrothermal Swing Adsorption

VSA : Vacuum Swing Adsorption

Supplementary Note 8. Comparison with existing electrothermal CO₂ capture systems

To contextualize the performance of the proposed CO₂ capture filter, a systematic comparison with recently reported Joule-heating-based electrothermal adsorbents was conducted (Supplementary Table 7). Prior ETSA studies have predominantly targeted either direct air capture (DAC) at 400 ppm or post-combustion flue gas at 5-15 vol% (50,000-150,000 ppm). To our knowledge, no previous study has applied Joule-heating-based regeneration to indoor CO₂ management at concentrations of 1,000-2,000 ppm.

Lee et al.¹⁰ demonstrated sorbent-coated carbon fibers for DAC using PEI-impregnated mesoporous silica, achieving 95% desorption in 10 min at 110 °C under 0.3 bar vacuum. Lee et al.¹¹ further advanced the electrified fiber concept using silver nanocomposite-coated EDA-grafted Y zeolite fibers, achieving a desorption temperature of 110 °C within 80 s with a partial vacuum-assisted four-step vacuum assisted ETSA cycle (90-min total desorption). Wu et al.¹² proposed a carbon nanofiber (CNF)-based PEI DAC air filter for building ventilation systems, with high uptake capacity (4.0 mmol g⁻¹ under 68% RH at 400 ppm) regenerable via Joule heating and solar thermal energy utilization. However, their system requires off-site regeneration with filter replacement every two days and transportation to centralized processing facilities.

In contrast, the present system achieves rapid desorption under atmospheric pressure, 95% regeneration within 15 min at 100 °C and within 35 min at 80 °C, without vacuum assistance. The favorable desorption kinetics observed in the present system can be attributed to the sorbent and the spray coating process. Lee et al.¹⁰ employed mesoporous silica (SYLOID C-803) in which PEI is confined within mesopore channels, creating substantial intra-particle diffusion resistance during CO₂ release. In the present work, nonporous silica nanoparticles (60-70 nm) were used, positioning the amine functional groups predominantly on the external particle surface and thereby minimizing the CO₂ diffusion pathway during thermal desorption. Additionally, the thin sorbent layer (14.7-46.1 μm) produced by spray coating provides direct thermal contact with the Joule-heated carbon fiber, enabling rapid and uniform heat delivery to the adsorbent. The elimination of vacuum pumps significantly simplifies the system design and removes the associated noise and energy penalty, which is an essential consideration for deployment in occupied indoor spaces.

The filter-scale CO₂ uptake of 1.26 mmol g⁻¹ (1.84 mmol g⁻¹ at the powder scale) under 1,000 ppm at 25 °C is comparable to or exceeds those of other fiber-based ETSA systems on a coated-fiber mass basis, such as 0.65 mmol g⁻¹ (Lee et al.¹⁰) and 0.39 mmol g⁻¹ (Lee et al.¹¹, Ag-coated fiber basis). The system also demonstrated superior cyclic stability, retaining full CO₂ capture capacity with a 2.28% increase over 200 adsorption-desorption cycles, compared to the 27.6% capacity loss within 40 cycles reported for the CNF-based adsorbent by Wu et al.¹². Finally, unlike all cited studies that remain at the material-level demonstration, this work extends to system-level validation by integrating the CO₂ capture filter with a demand-controlled ventilation (DCV) framework and deep learning-based real-time control,

achieving up to 28.3% ventilation energy savings compared to conventional DCV systems.

Among other state-of-the-art structured DAC sorbents, Wu et al.¹⁸ reported 0.71 mmol g⁻¹ at 400 ppm using PEI-impregnated silica on a ceramic substrate, though their system requires steam-assisted temperature vacuum swing adsorption (S-TVSA) with high-temperature steam supply, which is impractical for indoor applications.

It is also worth noting that alternative CO₂ capture strategies were considered but deemed unsuitable for the intended indoor application. Liquid amine scrubbing (e.g., aqueous MEA solutions) requires regeneration temperatures of 120-140 °C¹⁹ with reboiler duties of 3.8-4.2 GJ t⁻¹CO₂^{20,21}, and is known to emit volatile degradation products including ammonia, aldehydes, and potentially carcinogenic nitrosamines during thermal cycling²², posing unacceptable health risks in enclosed indoor spaces where stack-based atmospheric dispersion is unavailable. Metal-organic frameworks, while offering high surface areas and tunable pore structures, suffer from significant capacity reduction under humid conditions²³ and involve more complex and costly synthesis processes compared to commercially available amine-functionalized silica²⁴. Zeolite-based physisorbents typically require regeneration temperatures of 150-250 °C²⁵ and exhibit up to 93% capacity loss at 74% relative humidity²⁶, making them incompatible with the moderate-temperature, humidity-tolerant operation required for indoor environments.

After (Page 32-33):

Long-term cyclic stability test

To evaluate the long-term durability of the sorbent under repeated thermal cycling, 200 consecutive partial adsorption-desorption cycles were performed using a simultaneous thermogravimetric analyzer (HITACHI, STA 200). Each cycle consisted of a 20 min adsorption phase at 25 °C under a 1,000 ppm CO₂/N₂ gas flow, followed by desorption via heating to 100 °C at a ramp rate of 10 °C min⁻¹ with a 1 min isothermal hold. Because the instrument is limited to 100 programmable temperature steps (approximately 30 cycles per run), the 200-cycle test was completed by performing seven sequential runs under identical conditions.

After (Page 26-27):

A systematic comparison with recently reported Joule-heating-based CO₂ capture systems is provided in Supplementary Table 7 and Supplementary Note 8. Lee et al.¹ achieved 95% desorption in 10 min at 110 °C under 0.3 bar vacuum using PEI-impregnated mesoporous silica coated on carbon fibers for DAC. Lee et al.² developed silver nanocomposite-coated zeolite fibers with a partial vacuum-assisted e-TVSA cycle for DAC. Wu et al.³ proposed a carbon nanofiber-based DAC air filter for building ventilation, though requiring off-site regeneration with filter replacement every two days. All three studies target DAC at 400 ppm, whereas the present work applies Joule-heating-based regeneration to indoor CO₂ at 1,000-2,000 ppm. The proposed filter achieves vacuum-free desorption (95% within 15 min at 100 °C), enabled by nonporous silica nanoparticles that minimize intra-particle diffusion resistance and a thin sorbent layer (14.7–46.1 μm) ensuring direct thermal contact with the carbon fiber. The filter-scale uptake of 1.26 mmol g⁻¹ exceeds those of comparable fiber-based systems (0.65 mmol g⁻¹; 0.39 mmol g⁻¹), with stable cycling performance over 200 cycles (Supplementary Fig. 3).

3. Joule heating in this work may affect the indoor temperature or humidity, as shown in Figure 4f. When heating for desorption, both the temperature and RH increase, indicating that the moisture must be released to the indoor environment, causing the humidification effect. This effect also revealed that the adsorbent captures both water and CO₂ at the sorption stage. Therefore, what's the impact of relative humidity on carbon capture? The record of CO₂ capture capacity is tested under humid conditions? Therefore, you should keep the same humidity condition when conducting a performance comparison between materials and filter sorption/desorption?

Answer: We thank the reviewer for this valuable comment. As the reviewer pointed out, the performance of amine-functionalized CO₂ sorbents is strongly influenced by the presence of moisture in the air. In the present study, when desorption is carried out in the lab-scale closed system, both the CO₂ concentration and relative humidity inside the chamber increase due to the release of adsorbed CO₂ and H₂O. However, in the proposed ventilation system, the desorbed CO₂ and water molecules would be released outdoor rather than accumulated within the indoor space. Therefore, under actual operating conditions, a dehumidification effect rather than a humidification effect is expected during regeneration.

Furthermore, a breakthrough-type setup was not adopted in this study because it requires a relatively high pressure drop condition, which is not suitable for evaluating the performance of the fabricated filter. In addition, in an open system, it is difficult to accurately track the low-concentration CO₂ capture behavior. For these reasons, a closed-loop internal recirculation system was employed in this work. All performances presented in Figure 4 were evaluated under humid air conditions at around 40% RH.

Since it is practically difficult to maintain ultra-dry or humid conditions in a stable and controlled manner using the present lab-scale setup, additional measurements were conducted using a DVS-Carbon system, which allows precise humidity control while supplying low-concentration CO₂. Using this equipment, the CO₂ capture performance at 1,000 ppm was evaluated under 0–60% RH conditions. The CO₂/H₂O co-adsorption results confirmed that, as the relative humidity increased toward the high-humidity range, the CO₂ capture performance showed a decreasing trend. This result indicates that excessive moisture uptake under humid conditions can adversely affect CO₂ adsorption performance, which is consistent with the reviewer's concern. The further analysis results are reflected in both manuscript and Supplementary information.

After (Page 7):

Figure 3d presents the co-adsorption capacities of CO₂ and H₂O as a function of target relative humidity (RH) for the optimally loaded sorbent (50wt%). Given that the CO₂ adsorption capacity of amine-impregnated sorbents may vary substantially in the presence of water vapor, it was necessary to characterize co-adsorption behavior under controlled humidity conditions. In each measurement, the adsorbent was first pre-saturated with water vapor at a fixed target RH (0%, 20%, 40%, or 60%) under a N₂ carrier gas until mass equilibrium was achieved, after which 1,000 ppm CO₂ was introduced to evaluate the subsequent CO₂ uptake under steady-state humid conditions. H₂O adsorption capacity increased monotonically with target RH, reaching approximately 4.87, 10.46, and 16.61 mmol g⁻¹ at 20%, 40%, and 60% RH, respectively. CO₂ adsorption capacity, by contrast, exhibited a non-monotonic dependence on RH: a modest enhancement was observed at 20% RH relative to the dry condition, followed by a progressive decline at 40% RH and 60% RH

conditions. The initial enhancement at low humidity is attributed to a shift in the CO_2 reaction pathway, in which the introduction of moderate water vapor promotes the partial conversion from ammonium carbamate to bicarbonate and carbonate species, increasing the effective amine utilization efficiency and thereby enhancing CO_2 uptake¹⁷. At higher humidity levels, however, the accumulation of water within the pore network progressively impedes CO_2 diffusion and occupies adsorption sites in competition with CO_2 molecules, leading to the observed decline in uptake¹⁸. These results suggest that under indoor conditions exceeding approximately 40% RH, competitive adsorption between H_2O and CO_2 may substantially reduce the CO_2 capture performance of the amine-impregnated sorbent. Each co-adsorption measurement was conducted over three consecutive cycles, and the full adsorption curves for all RH conditions are provided in Supplementary Fig. 2.

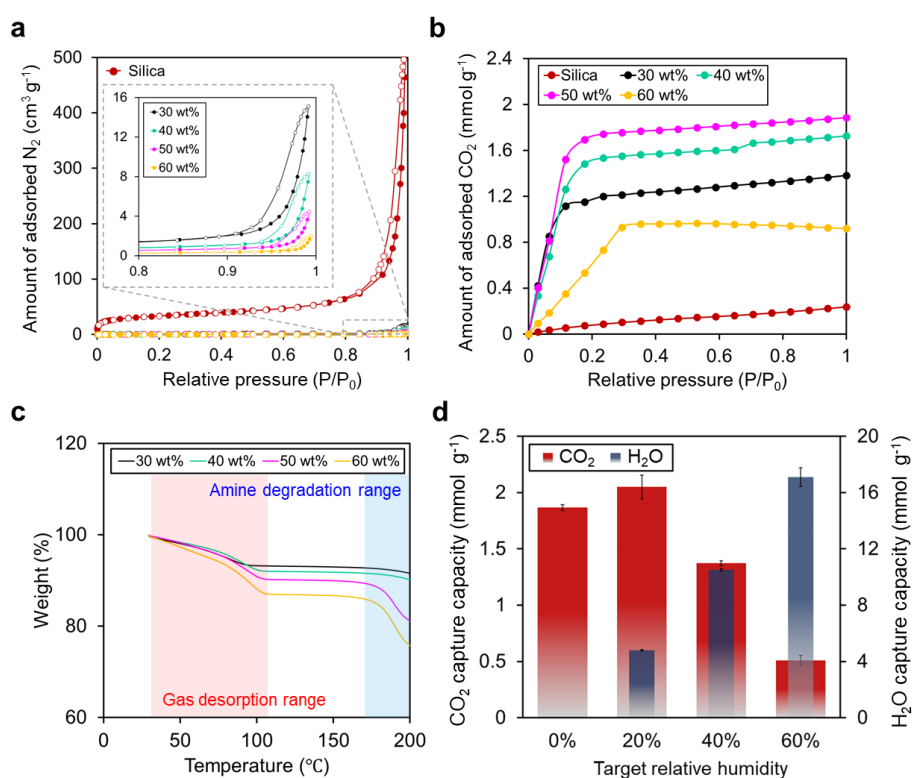
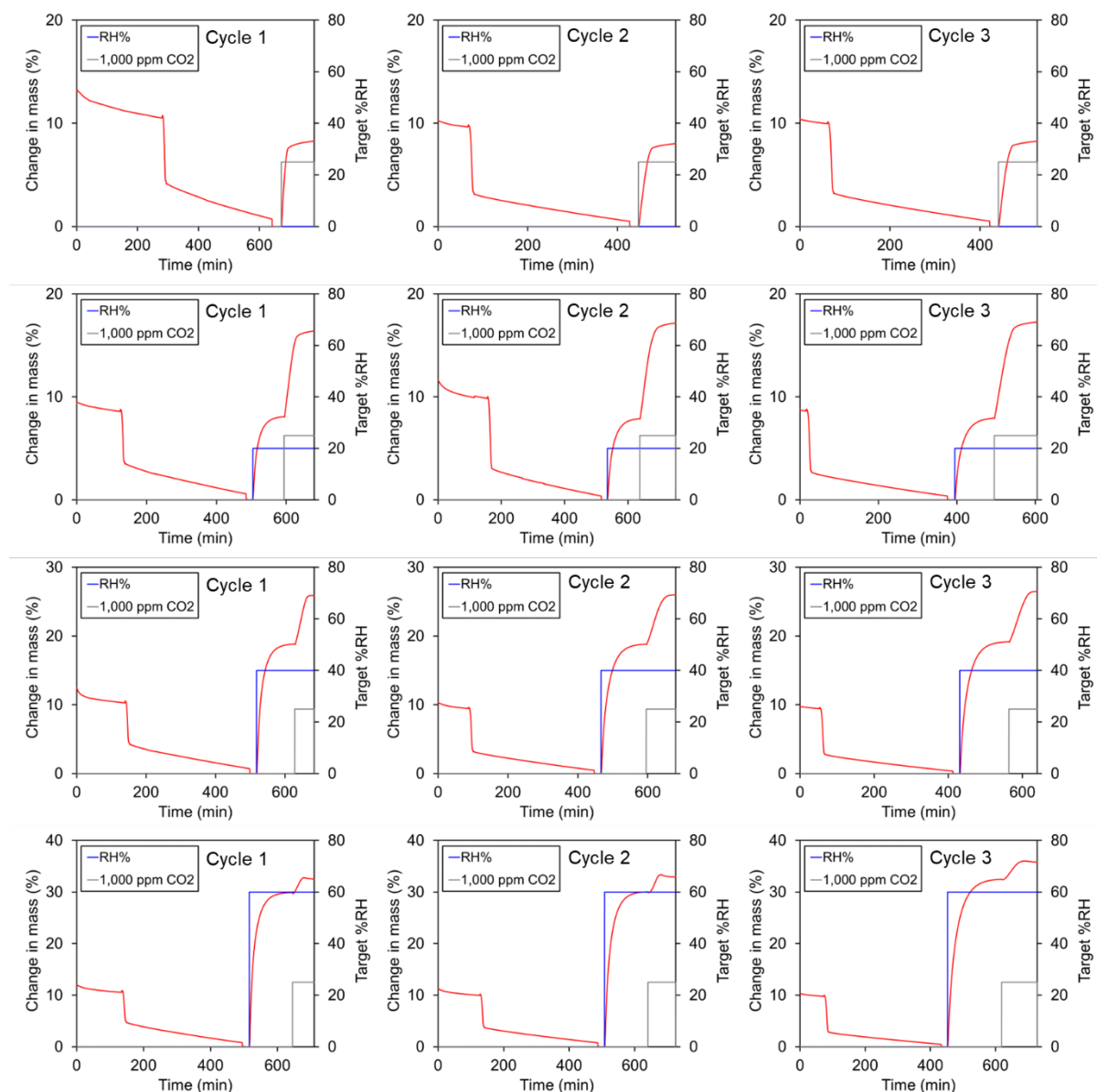


Fig. 3. Characterization data of CO₂ adsorbent (Silica nanopowder). (a) N₂ adsorption curve (b) CO₂ adsorption curve depending on the partial pressure. (c) Thermogravimetric analysis result of the samples. (d) CO₂ and H₂O co-adsorption analysis results.

Supplementary information



Supplementary Fig. 2. Full dynamic vapor-carbon sorption mass-change profiles for co-adsorption of H₂O and CO₂ (1,000 ppm) under target relative humidity conditions of 0%, 20%, 40%, and 60% RH.

After (Page 31):

Characterization

The structural properties of the adsorbents were analyzed using a Brunauer–Emmett–Teller (BET) analyzer (Micromeritics TriStar II 3020) via N₂ adsorption at −195.9 °C to determine surface area and pore characteristics. CO₂ adsorption measurements were performed using the same instrument by switching the adsorbate gas from N₂ to pure CO₂, enabling comparative analysis under different gas environments. Thermal stability and decomposition behavior were evaluated by thermogravimetric analysis (TGA) under N₂ atmosphere.

Samples were heated from 25 °C to 600 °C at a rate of 10 °C/min to assess moisture content, thermal degradation, and residual mass. Surface morphology and particle size were examined via field-emission scanning electron microscopy (FE-SEM, Quanta FEG 240). Prior to imaging, a platinum coating was applied (20 mA, 90 s) to reduce charging effects. Elemental composition was determined using energy-dispersive X-ray spectroscopy (EDS), with data averaged over three measurements taken at varying resolutions for reliability. The H₂O and CO₂ co-adsorption behavior was characterized using a DVS-Carbon instrument (Surface Measurement Systems) at 25 °C with a dm/dt threshold of 0.005 % min⁻¹. Prior to each measurement, samples were regenerated at 90 °C under dry conditions, followed by stabilization at 25 °C. CO₂ uptake was then evaluated by exposing samples to 1,000 ppm CO₂ at relative humidity levels of 0, 20, 40, and 60% RH.

4. The results may be different under different humidity conditions? Such as Figures 4c and 4d.

Answer: This comment appears to be raised in a similar context to Comment 3. In practice, it is difficult to establish precise initial conditions in a lab-scale closed chamber by simultaneously controlling humidity, temperature, and CO₂ concentration. In response to the reviewer's request, and as the most appropriate approach available to the authors, the CO₂ adsorption behavior under precisely controlled humidity conditions was evaluated using a DVS-Carbon system. More specifically, the tendency of CO₂ uptake after prior H₂O adsorption was assessed based on the mass change of the sample. As this point is closely related to Comment 3, the corresponding results have already been provided there. We thank the reviewer for this valuable comment.

5. Some abbreviations should be explained when you first use them, such as HEPA, RMSE, MAE...

Answer: We appreciate reviewer's detailed comments. We have now addressed the missing explanations for the abbreviations used in the text.

Before:

However, its applicability to actual ventilation systems is limited due to the high pressure drop, since these systems already incorporate pressure-inducing components such as HEPA filters and heat exchangers. In this study, the performance of the carbon fiber CO₂ capture filter was assessed using a batch-type acrylic chamber setup (Fig. 4a), which facilitates internal air circulation, continuous monitoring of CO₂ concentration, and simulates filter placement in realistic ventilation environments.

After (Page 12):

However, its applicability to actual ventilation systems is limited due to the high pressure drop, since these systems already incorporate pressure-inducing components such as High Efficiency Particulate Air (HEPA) filters and heat exchangers. In this study, the performance of the carbon fiber CO₂ capture filter was assessed using a batch-type acrylic chamber setup (Fig. 4a), which facilitates internal air circulation, continuous monitoring of CO₂ concentration, and simulates filter placement in realistic ventilation environments.

Before:

DCV systems, which use indoor CO₂ concentrations as indicators of occupancy and air quality, are widely employed to optimize HVAC energy consumption¹⁹. These systems adjust outdoor air intake in response to real-time CO₂ levels, thereby minimizing unnecessary ventilation while maintaining acceptable indoor air quality (IAQ).

After (Page 16):

DCV systems, which use indoor CO₂ concentrations as indicators of occupancy and air quality, are widely employed to optimize **heating, ventilation and air conditioning (HVAC)** energy consumption¹⁹. These systems adjust outdoor air intake in response to real-time CO₂ levels, thereby minimizing unnecessary ventilation while maintaining acceptable indoor air quality (IAQ).

Before:

During the FCDNN training phase, Bayesian optimization was employed to identify the most effective combination of hyperparameters, such as the number of hidden layers, the number of neurons in each layer, and the batch size, by minimizing the combined error metric of RMSE and MAE.

After (Page 18):

During the FCDNN training phase, Bayesian optimization was employed to identify the most effective combination of hyperparameters, such as the number of hidden layers, the number of neurons in each layer, and the batch size, by minimizing the combined error metric of **Root Mean Square Error (RMSE) and Mean Absolute Error (MAE)**.

Reviewer #2 (Remarks to the Author):

This manuscript explores a new approach to indoor air quality management by integrating a CO₂ capture filter with a demand-controlled ventilation (DCV) system. The filter is made from amine-functionalized silica coated onto carbon fiber, enabling regeneration via Joule heating. The study spans material synthesis, lab-scale characterization, electrothermal analysis, and system-level simulations, including optimization and deep learning-assisted predictive control. The authors report energy savings of up to ~28% compared to conventional DCV systems and propose strategies to further reduce energy consumption. The work is ambitious in scope, aiming to connect low-concentration CO₂ capture materials with practical building applications, providing a multi-scale perspective from adsorbent properties to system-level performance.

There are several critical issues that limit the manuscript's current suitability for publication:

1. The CO₂ uptake of the coated filter (1.26 mmol/g) is lower than comparable amine-based sorbents in the literature (2–3 mmol/g). This reduction raises questions about practical performance at building scale.

Answer: We thank the reviewer for raising this important point. The CO₂ uptake values of 2-3 mmol g⁻¹ cited by the reviewer are typically reported for amine-based sorbents in powder form under conditions that differ from those used in the present study. We would like to address this concern from three perspectives.

First, regarding the intrinsic sorbent performance, the amine-impregnated silica powder developed in this study exhibits a CO₂ uptake of 1.84 mmol g⁻¹ under 1,000 ppm CO₂ at 25 °C. It should be noted that the 2-3 mmol/g values are frequently measured under higher CO₂ partial pressures (e.g., 5–15 vol%) or under conditions optimized for maximum equilibrium capacity, which are not representative of the indoor CO₂ concentration range (1,000-2,000 ppm) targeted in this study.

Second, the reduction from 1.84 mmol g⁻¹ (powder) to 1.26 mmol g⁻¹ (coated sorbent) represents a 31.5% decrease, which is an inherent and well-documented consequence of transitioning from powder to structured form. As discussed in the manuscript (Fig. 5d), this decline is attributed to dilution of amine content during slurry preparation, structural changes during high-pressure spray deposition, and non-uniform coating distribution that limits effective surface interaction. Importantly, this capacity reduction upon structuring is not unique to the present system but is universally observed across the CO₂ capture literature. For instance, Wu et al.²⁰ reported 0.71 mmol g⁻¹ at 400 ppm for PEI-impregnated silica coated on ceramic via dip coating, Grossmann et al.²¹ reported 0.44 mmol g⁻¹ (pellet) and 0.40 mmol g⁻¹ (monolith) at 400 ppm for triamine-grafted alumina, and Huang et al.²² reported 1.48 mmol g⁻¹ at 2 vol% CO₂ for TEPA-impregnated silica gel pellets with a microcrystalline cellulose binder. In this context, the filter-scale uptake of 1.26 mmol g⁻¹ achieved in the present work at 1,000 ppm is competitive with or exceeds these structured sorbent benchmarks, particularly considering that many of the cited values were measured at higher CO₂ concentrations.

Third, for practical building-scale applications, the effective working capacity under cyclic partial regeneration is more operationally relevant than the equilibrium saturation capacity. The filter exhibited superior initial adsorption kinetics compared to the powder form within the first 30 minutes (Fig. 5d), which is attributed to lower film diffusion resistance and

thinner boundary layers in the fiber-aligned structure. This kinetic advantage is particularly beneficial for indoor applications where rapid CO₂ removal during short capture intervals is more critical than maximizing absolute equilibrium capacity.

In response to the reviewer's comment, we have added a discussion of structured sorbent performance benchmarks in the revised Supplementary Information (Supplementary Note 8 and Supplementary Table 7) to provide a more comprehensive comparison.

Supplementary information

After:

Supplementary Table 7. Comparison of electrothermal CO₂ adsorbents with Joule-heating regeneration

Sorbent	Form factor	Heating element	Regeneration Method	Target Application	T _{ads} (K)	T _{des} (K)	t _{des} (min)	CO ₂ Uptake (mmol g ⁻¹)	Cyclic Stability	Ref
PEI/mesoporous silica	Powder coated fiber	Carbon fiber	ETSA VSA	+DAC (400 ppm)	30°C	90-110°C	19min (95%, vacuum-assisted)	0.65 (Filter, 400ppm)	10 cycles	¹
EDA-grafted zeolite	Y Powder coated fiber	Silver nanocomposite	ETSA VSA	+DAC (400 ppm)	25°C	110°C	90min cycle (desorption)	0.39-0.41 (Fiber, 400ppm)	4 cycles (dry, 5% loss) 10 cycles (humid, 12% loss)	²
PEI/carbon nanofiber	Nonwoven filter	Carbon fiber	ETSA + Solar thermal	Distributed DAC (400 ppm)	25°C	80-105°C	1-2s Joule Heating + ~30min Solar Thermal	1.5 (Filter, 400ppm)	70 cycles (27.6% loss at 40cycles, then stable)	³
Amine-based ion exchange resin/Ag-coated glass flakes	3D-printed monolith	Ag-coated glass flakes	ETSA	DAC (400 ppm)	25°C	70°C	~1 min Joule Heating + ~60 min cycle	1.5 (Monolith, 9vol%, Dry) 0.5 (Monolith, 400ppm, Dry)	10 cycles	⁴
PEI/mesoporous carbon spheres	Spherical particles	Mesoporous carbon spheres	ETSA	Post-combustion (5-15%)	75°C	110°C	30min (ETSA)	3.7 (Powder, 15% CO₂, 75°C, Dry) 4.3 (Powder, 15% CO₂, 75°C, RH 60%)	10 cycles (3% loss)	⁵
SiC-PEI fiber CNT-zeolite fiber	Hollow fiber bundle	SiC or CNT	ETSA VSA	+Post-combustion (15%)	30°C	80-140°C	N/A	0.19 (SiC-PEI, 15% CO₂, Dry) 2.32 (CNT-zeolite, Fiber, 15% CO₂, Dry)	N/A	⁶
Zeolite nanocrystals/carbon foam	Ti-Beta Microcellular foam	Carbon foam	ETSA	Post-combustion (0.15-1bar)	25°C	90-200°C	20min (87%, vacuum-free)	4.6 (Powder, 1bar)	30 cycles (30% loss)	⁷
Zeolite NaUSY/activated carbon	Extruded monolith	Activated carbon	ETSA	Post-combustion (<10% CO ₂)	30°C	100-150°C	N/A	2.23 (Monolith, 20kPa)	N/A	⁸

PEI/nonporous silica	Powder	Carbon fiber	ETSA	Indoor (1000-2000ppm)	25°C	60-100°C	15min (95%, vacuum-free)	100°C,	1.84 (Powder, 1000ppm)	200 cycles (2.4% mass loss, no capacity loss)
	coated fiber						35min (95%, vacuum-free)	80°C,	1.26 (Filter, 1000ppm)	

PEI : Polyethylenimine

EDA : Ethylenediamine

ETSA : Electrothermal Swing Adsorption

VSA : Vacuum Swing Adsorption

Supplementary Note 8. Comparison with existing electrothermal CO₂ capture systems

To contextualize the performance of the proposed CO₂ capture filter, a systematic comparison with recently reported Joule-heating-based electrothermal adsorbents was conducted (Supplementary Table 7). Prior ETSA studies have predominantly targeted either direct air capture (DAC) at 400 ppm or post-combustion flue gas at 5-15 vol% (50,000-150,000 ppm). To our knowledge, no previous study has applied Joule-heating-based regeneration to indoor CO₂ management at concentrations of 1,000-2,000 ppm.

Lee et al.¹⁰ demonstrated sorbent-coated carbon fibers for DAC using PEI-impregnated mesoporous silica, achieving 95% desorption in 10 min at 110 °C under 0.3 bar vacuum. Lee et al.¹¹ further advanced the electrified fiber concept using silver nanocomposite-coated EDA-grafted Y zeolite fibers, achieving a desorption temperature of 110 °C within 80 s with a partial vacuum-assisted four-step vacuum assisted ETSA cycle (90-min total desorption). Wu et al.¹² proposed a carbon nanofiber (CNF)-based PEI DAC air filter for building ventilation systems, with high uptake capacity (4.0 mmol g⁻¹ under 68% RH at 400 ppm) regenerable via Joule heating and solar thermal energy utilization. However, their system requires off-site regeneration with filter replacement every two days and transportation to centralized processing facilities.

In contrast, the present system achieves rapid desorption under atmospheric pressure, 95% regeneration within 15 min at 100 °C and within 35 min at 80 °C, without vacuum assistance. The favorable desorption kinetics observed in the present system can be attributed to the sorbent and the spray coating process. Lee et al.¹⁰ employed mesoporous silica (SYLOID C-803) in which PEI is confined within mesopore channels, creating substantial intra-particle diffusion resistance during CO₂ release. In the present work, nonporous silica nanoparticles (60-70 nm) were used, positioning the amine functional groups predominantly on the external particle surface and thereby minimizing the CO₂ diffusion pathway during thermal desorption. Additionally, the thin sorbent layer (14.7-46.1 μm) produced by spray coating provides direct thermal contact with the Joule-heated carbon fiber, enabling rapid and uniform heat delivery to the adsorbent. The elimination of vacuum pumps significantly simplifies the system design and removes the associated noise and energy penalty, which is an essential consideration for deployment in occupied indoor spaces.

The filter-scale CO₂ uptake of 1.26 mmol g⁻¹ (1.84 mmol g⁻¹ at the powder scale) under 1,000 ppm at 25 °C is comparable to or exceeds those of other fiber-based ETSA systems on a coated-fiber mass basis, such as 0.65 mmol g⁻¹ (Lee et al.¹⁰) and 0.39 mmol g⁻¹ (Lee et al.¹¹, Ag-coated fiber basis). The system also demonstrated superior cyclic stability, retaining full CO₂ capture capacity with a 2.28% increase over 200 adsorption-desorption cycles,

compared to the 27.6% capacity loss within 40 cycles reported for the CNF-based adsorbent by Wu et al.¹². Finally, unlike all cited studies that remain at the material-level demonstration, this work extends to system-level validation by integrating the CO₂ capture filter with a demand-controlled ventilation (DCV) framework and deep learning-based real-time control, achieving up to 28.3% ventilation energy savings compared to conventional DCV systems.

Among other state-of-the-art structured DAC sorbents, Wu et al.¹⁸ reported 0.71 mmol g⁻¹ at 400 ppm using PEI-impregnated silica on a ceramic substrate, though their system requires steam-assisted temperature vacuum swing adsorption (S-TVSA) with high-temperature steam supply, which is impractical for indoor applications.

It is also worth noting that alternative CO₂ capture strategies were considered but deemed unsuitable for the intended indoor application. Liquid amine scrubbing (e.g., aqueous MEA solutions) requires regeneration temperatures of 120-140 °C¹⁹ with reboiler duties of 3.8-4.2 GJ t⁻¹CO₂^{20,21}, and is known to emit volatile degradation products including ammonia, aldehydes, and potentially carcinogenic nitrosamines during thermal cycling²², posing unacceptable health risks in enclosed indoor spaces where stack-based atmospheric dispersion is unavailable. Metal-organic frameworks, while offering high surface areas and tunable pore structures, suffer from significant capacity reduction under humid conditions²³ and involve more complex and costly synthesis processes compared to commercially available amine-functionalized silica²⁴. Zeolite-based physisorbents typically require regeneration temperatures of 150-250 °C²⁵ and exhibit up to 93% capacity loss at 74% relative humidity²⁶, making them incompatible with the moderate-temperature, humidity-tolerant operation required for indoor environments.

2. Long-term stability tests are limited to 10–20 cycles. Real HVAC systems operate over months to years, and the manuscript does not address the effects of thermal cycling, humidity, dust, or potential amine leaching.

Answer: We thank the reviewer for this critical comment regarding long-term durability. We fully agree that extended cycling tests and environmental robustness assessments are essential for practical HVAC deployment. In response, we have conducted additional experiments addressing each of the concerns raised.

Thermal cycling stability (200 cycles)

Extended adsorption–desorption cycling tests were performed over 200 cycles at a regeneration temperature of 100 °C using thermogravimetric analysis (TGA). As shown in Supplementary Fig. 3, the sorbent exhibited stable cyclic performance, with the CO₂ capture capacity increasing slightly by 2.28% from the first to the last cycle despite a modest overall mass decrease of 2.36%. The results confirm that the operating temperature range of 80–100 °C employed in this study is well below the amine thermal degradation threshold (~150 °C, Fig. 3c), ensuring minimal performance degradation over extended operation. Given that no measurable capacity decline was observed even at the highest regeneration temperature tested, lower regeneration temperatures are expected to yield comparable or improved long-term durability.

Humidity effects

To systematically evaluate the effect of humidity on CO₂ adsorption performance, co-adsorption measurements of CO₂ and H₂O were conducted using a DVS-Carbon system,

which enables precise control of both relative humidity and CO₂ concentration. In each measurement, the sorbent was first pre-saturated with water vapor at a fixed target RH (0%, 20%, 40%, or 60%) under N₂ carrier gas until mass equilibrium was achieved, after which 1,000 ppm CO₂ was introduced at 25 °C to evaluate the subsequent CO₂ uptake (Fig. 3d). H₂O adsorption capacity increased monotonically with target RH, reaching approximately 4.87, 10.46, and 16.61 mmol/g at 20%, 40%, and 60% RH, respectively. CO₂ adsorption capacity exhibited a non-monotonic dependence on RH: a modest enhancement was observed at 20% RH relative to the dry condition, attributed to the promotion of bicarbonate and carbonate formation pathways that increase effective amine utilization efficiency. At higher humidity levels (40% and 60% RH), however, competitive adsorption between H₂O and CO₂ led to a progressive decline in CO₂ uptake. These results confirm that the sorbent maintains robust CO₂ capture performance within the typical indoor humidity range of 40-60% RH, while also identifying the onset of competitive adsorption effects that should be considered in system design for high-humidity environments.

Dust exposure

In practical building ventilation systems, the CO₂ capture filter is positioned downstream of a High Efficiency Particulate Air (HEPA) filter, which removes more than 99.97% of airborne particulates $\geq 0.3 \mu\text{m}$. This pre-filtration configuration effectively prevents dust accumulation on the sorbent surface, minimizing the risk of pore blockage or performance degradation due to particulate fouling.

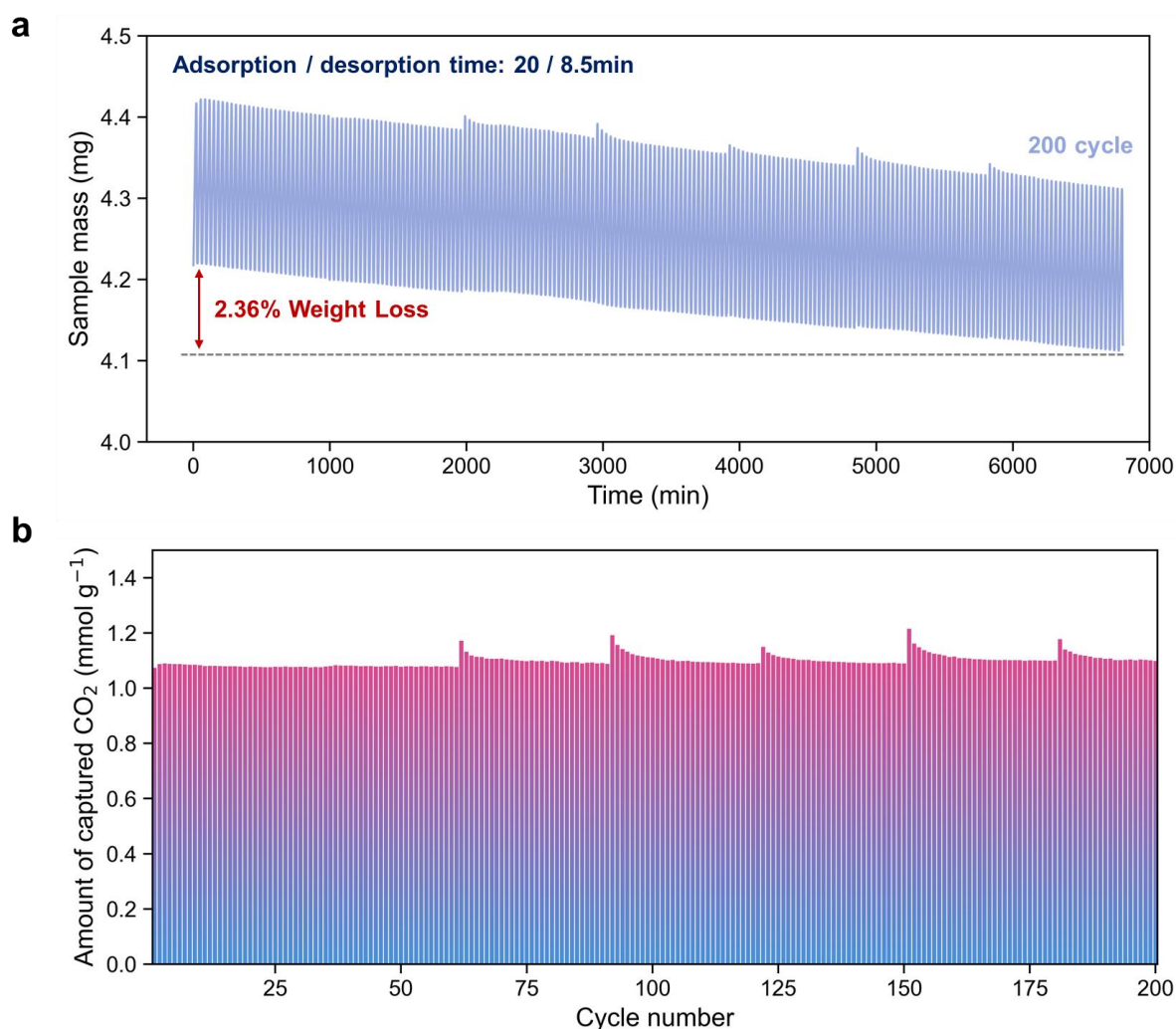
Amine leaching

The thermogravimetric analysis presented in Fig. 3c demonstrates that no significant irreversible weight loss occurs below 150 °C for the 50 wt% amine-loaded sorbent, confirming that amine volatilization or leaching is negligible within the operating temperature range (80–100 °C). This is further supported by the extended 200-cycle TGA results (Supplementary Fig. 3), in which the total sample mass decreased by only 2.36% over the entire test duration. Importantly, this minor mass reduction did not translate into a loss of CO₂ capture performance; the capacity per unit mass increased slightly from 1.074 to 1.098 mmol g⁻¹ (+2.28%) from the first to the last cycle, indicating that the observed mass change is not attributable to the loss of active amine species. The consistent adsorption capacity across 200 cycles provides strong evidence that amine loss through leaching or evaporation is minimal under the tested conditions.

In summary, these additional experiments demonstrate that the proposed filter system exhibits robust long-term stability under thermal cycling, maintains performance across varying humidity conditions, and benefits from inherent protection against dust and amine leaching through system design and material properties. The corresponding data and discussion have been incorporated into the revised manuscript and Supplementary Information.

After (Page 7):

Furthermore, to assess the long-term durability of the sorbent under extended thermal cycling, 200 consecutive adsorption–desorption cycles were conducted at a regeneration temperature of 100 °C (Supplementary Fig. 3). Despite a modest overall mass decrease of 2.36% over the entire test, the CO₂ capture capacity per unit mass showed no degradation, increasing slightly from 1.074 to 1.098 mmol g⁻¹ (+2.28%), confirming the sorbent's suitability for sustained long-term operation.



Supplementary Fig. 3. Long-term cyclic stability of the sorbent-coated carbon fiber filter over 200 adsorption-desorption cycles at regeneration temperature of 100 °C. (a) Thermogravimetric (TG) curve showing the sample mass variation across 200 cycles (b) Amount of captured CO₂ per cycle

After (Page 32-33):

Long-term cyclic stability test

To evaluate the long-term durability of the sorbent under repeated thermal cycling, 200 consecutive partial adsorption–desorption cycles were performed using a simultaneous thermogravimetric analyzer (HITACHI, STA 200). Each cycle consisted of a 20 min adsorption phase at 25 °C under a 1,000 ppm CO₂/N₂ gas flow, followed by desorption via heating to 100 °C at a ramp rate of 10 °C min^{−1} with a 1 min isothermal hold. Because the instrument is limited to 100 programmable temperature steps (approximately 30 cycles per run), the 200-cycle test was completed by performing seven sequential runs under identical conditions.

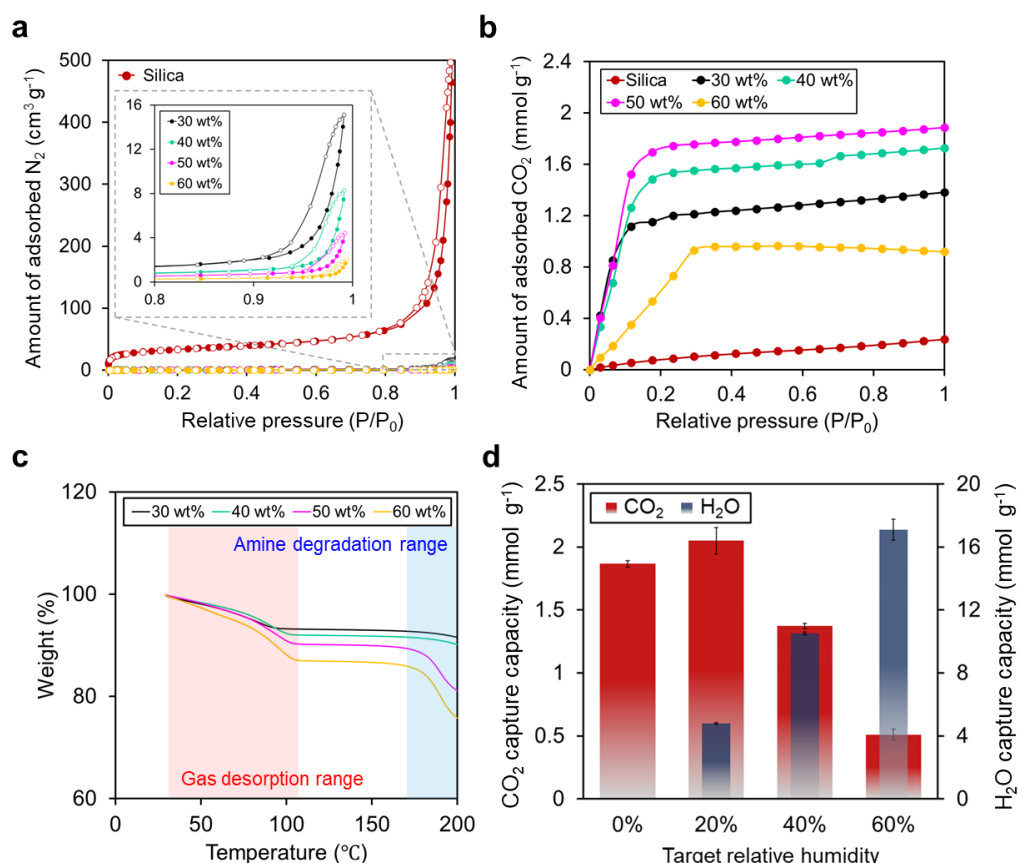


Fig. 3. Characterization data of CO₂ adsorbent (Silica nanopowder). (a) N₂ adsorption curve (b) CO₂ adsorption curve depending on the partial pressure. (c) Thermogravimetric analysis result of the samples. (d) CO₂ and H₂O co-adsorption analysis results.

3. Mechanical robustness is not assessed. Spray-coated silica on carbon fiber may delaminate or degrade under airflow-induced vibration, which is critical for real-world application.

Answer: We agree with the reviewer that evaluating the mechanical robustness of the coated carbon fiber is an essential analytical component when proposing real-world applications. In accordance with the reviewer's comment, we conducted both a bending test and an airflow exposure test. For the bending test, a 60 mm section at the midpoint of a 100 mm carbon fiber strip was coated and fixed to a bending test apparatus, and cyclic bending was applied at a bending radius of 15 mm. The mass was measured 10 times every 1,000 cycles, and a total of 10,000 cycles were performed. For the airflow exposure test, the coated carbon fiber was placed at a measurement point with an airflow velocity of approximately 2.2 m/s, and the mechanical durability was assessed by measuring the mass difference before and after 14 days of airflow exposure. The results of the mechanical robustness tests have been incorporated into both the manuscript and Supplementary Information.

After (Page 8):

The mechanical robustness of the silica-coated carbon fiber was evaluated through cyclic bending and airflow exposure tests (Supplementary Figs. 6 and 7). In the bending test, the

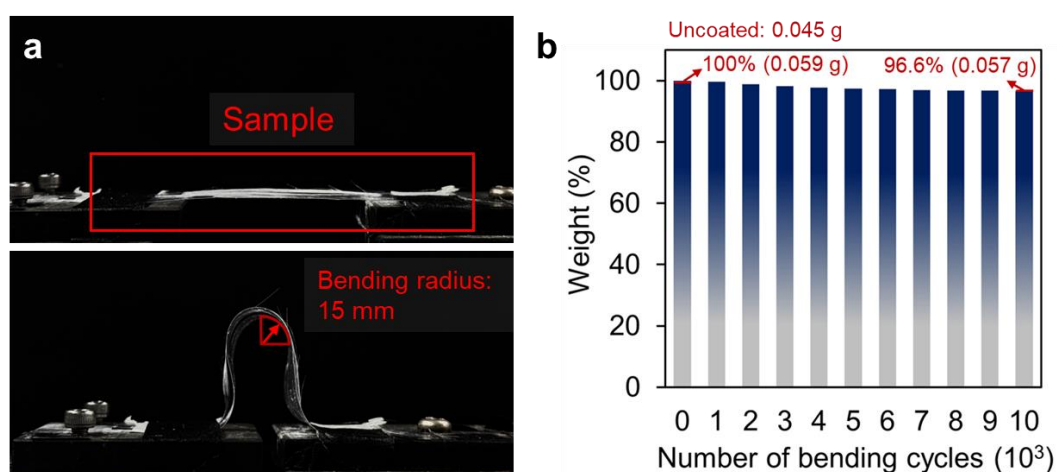
silica coating constituted 31.1% of the initial fiber mass, and after 10,000 bending cycles at a bending radius of 15 mm, the retained coating corresponded to 26.7% of the fiber mass, representing a coating loss of approximately 14.3%. In the airflow exposure test, the initial coating accounted for 44.8% of the fiber mass, and after 14 days of continuous airflow exposure at 2.2 m s^{-1} , the retained coating was 42.9% of the fiber mass, corresponding to a coating loss of approximately 4.3%. Given an assumed performance degradation rate of approximately 4% per week, the replacement interval can be logically defined based on a threshold retention of the initial performance rather than on an arbitrary fixed period. If the replacement criterion is set at 85–95% of the initial performance, a replacement interval of less than one month is recommended to maintain reliable performance under real-world operating conditions.

After (Page 31):

Mechanical robustness test

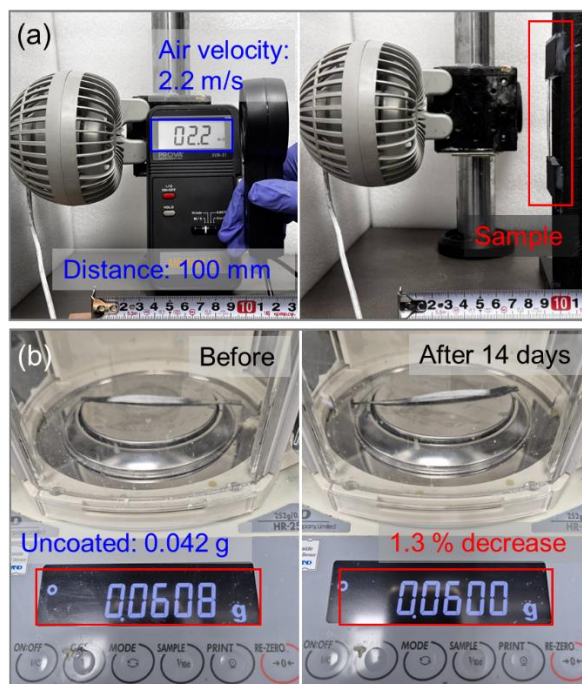
The mechanical robustness of the silica-coated carbon fiber was assessed through two durability tests: a cyclic bending test and an airflow exposure test. For the bending test, a 60 mm section at the midpoint of a 100 mm carbon fiber strip was coated and mounted on a bending test machine (Ocean Science, Republic of Korea). Cyclic bending was applied at a bending radius of approximately 15 mm and a speed of 20 mm/s for a total of 10,000 cycles, with the mass measured at every 1,000-cycle interval to monitor coating loss. For the airflow exposure test, the coated carbon fiber was placed 100 mm from a mini fan (Xiamen Golden Uyuan Electronic Co., Ltd., A1-036299, China), generating an airflow velocity of approximately 2.2 m/s as measured by an anemometer (PROVA Instruments Inc., AVM-01, Taipei). The sample was exposed to continuous airflow for 14 days, and the mass was recorded before and after the exposure period to assess the degree of coating delamination. Both tests were conducted to verify the structural integrity of the silica coating under mechanical and aerodynamic stresses relevant to practical operating conditions.

After (Supplementary information - Page 6):



Supplementary Fig. 6. Cyclic bending test of the silica-coated carbon fiber. (a) Photographs of the sample mounted on the bending test apparatus in the unbent (top) and bent (bottom) states. **(b)** Normalized weight retention of the coated carbon fiber.

After (Supplementary information - Page 7):



Supplementary Fig. 7. Airflow exposure test of the silica-coated carbon fiber. (a) Photographs of the experimental setup (b) Mass measurements of the coated carbon fiber.

4. The impact of indoor humidity on adsorption/desorption performance is insufficiently addressed, despite water uptake being briefly mentioned.

Answer: As the reviewer pointed out, although water uptake was measured under indoor conditions in the main text, the impact of indoor humidity on the adsorption & desorption performance was not discussed in detail. In the present study, the lab-scale experimental setup operated as a closed-loop system, in which adsorption and desorption were repeated in a sealed state once the initial conditions of temperature, RH, and CO₂ concentration were established. Because of this design, it was difficult to precisely control the initial state. As suggested by the reviewer, the CO₂ capture performance under different humidity conditions was further evaluated using a dynamic vapor-carbon sorption instrument, which allows precise RH control. The results showed that the CO₂ capture performance increased under 20% RH compared with the 0% RH dry-air condition. However, above this level, the CO₂ uptake gradually decreased as the moisture content in the air increased, indicating competitive adsorption between H₂O and CO₂. This result suggests that CO₂ capture performance may become limited above a certain RH level.

The corresponding analysis has been incorporated into the manuscript and the Supplementary information to address the reviewer's concern as thoroughly as possible. We thank the reviewer again for this valuable comment.

After (Page 7):

Figure 3d presents the co-adsorption capacities of CO₂ and H₂O as a function of target

relative humidity (RH) for the optimally loaded sorbent (50wt%). Given that the CO₂ adsorption capacity of amine-impregnated sorbents may vary substantially in the presence of water vapor, it was necessary to characterize co-adsorption behavior under controlled humidity conditions. In each measurement, the adsorbent was first pre-saturated with water vapor at a fixed target RH (0%, 20%, 40%, or 60%) under a N₂ carrier gas until mass equilibrium was achieved, after which 1,000 ppm CO₂ was introduced to evaluate the subsequent CO₂ uptake under steady-state humid conditions. H₂O adsorption capacity increased monotonically with target RH, reaching approximately 4.87, 10.46, and 16.61 mmol g⁻¹ at 20%, 40%, and 60% RH, respectively. CO₂ adsorption capacity, by contrast, exhibited a non-monotonic dependence on RH: a modest enhancement was observed at 20% RH relative to the dry condition, followed by a progressive decline at 40% RH and 60% RH conditions. The initial enhancement at low humidity is attributed to a shift in the CO₂ reaction pathway, in which the introduction of moderate water vapor promotes the partial conversion from ammonium carbamate to bicarbonate and carbonate species, increasing the effective amine utilization efficiency and thereby enhancing CO₂ uptake¹⁷. At higher humidity levels, however, the accumulation of water within the pore network progressively impedes CO₂ diffusion and occupies adsorption sites in competition with CO₂ molecules, leading to the observed decline in uptake¹⁸. These results suggest that under indoor conditions exceeding approximately 40% RH, competitive adsorption between H₂O and CO₂ may substantially reduce the CO₂ capture performance of the amine-impregnated sorbent. Each co-adsorption measurement was conducted over three consecutive cycles, and the full adsorption curves for all RH conditions are provided in Supplementary Fig. 2.

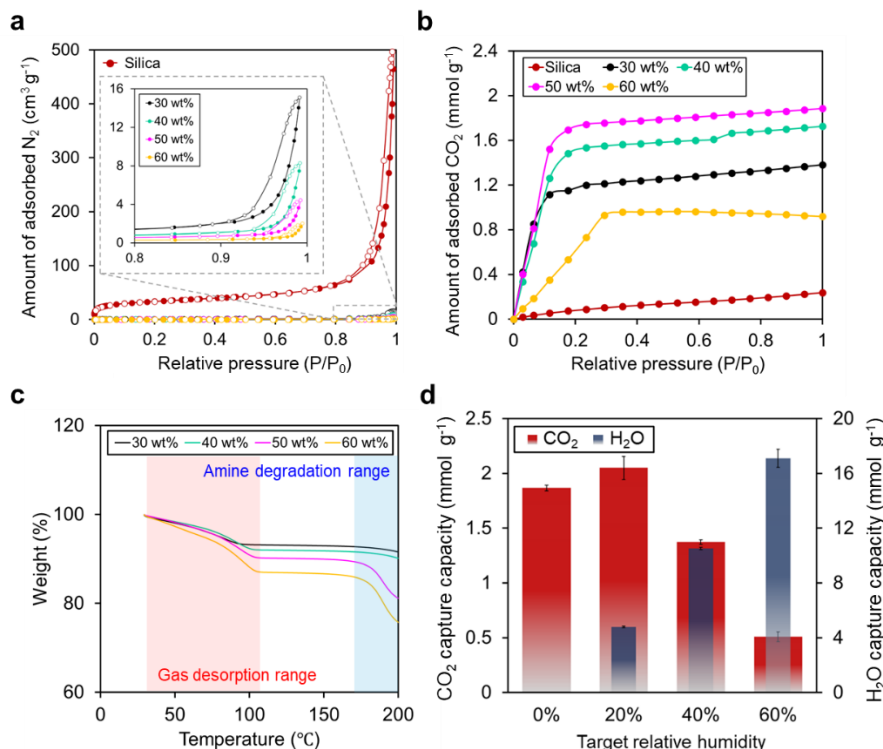
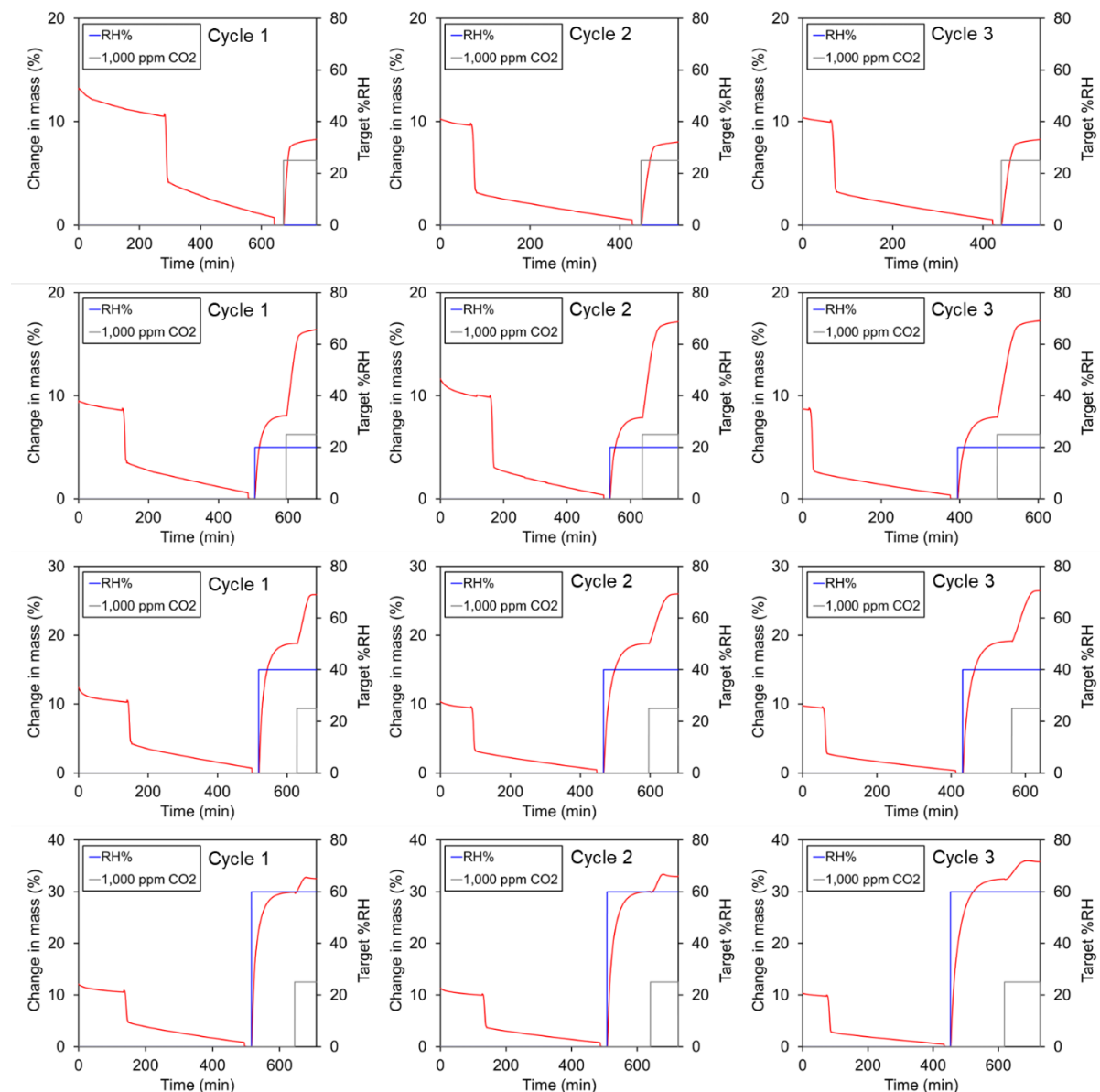


Fig. 3. Characterization data of CO₂ adsorbent (Silica nanopowder). (a) N₂ adsorption curve (b) CO₂ adsorption curve depending on the partial pressure. (c) Thermogravimetric analysis result of the samples. (d) CO₂ and H₂O co-adsorption analysis results.

Supplementary information



Supplementary Fig. 2. Full dynamic vapor-carbon sorption mass-change profiles for co-adsorption of H₂O and CO₂ (1,000 ppm) under target relative humidity conditions of 0%, 20%, 40%, and 60% RH.

5. Joule heating is demonstrated only at lab scale (10×10 mm plates). Scaling to real building modules introduces uncertainties in power distribution, safety, and system integration, potentially causing uneven desorption.

Answer: We thank the reviewer for this important comment regarding scalability. We would like to clarify that the dimension "10 mm × 10 mm" in the original manuscript was a typographical error, which has been corrected to 100 mm × 100 mm in the revised manuscript. As shown in Supplementary Fig. 4, the sorbent-coated carbon fiber sample used for coating characterization (SEM and EDS analysis) was prepared on a 100 mm × 100 mm acrylic plate. The actual CO₂ capture filter tested in this study consists of 8 cells with a fiber length of 53 cm per cell, installed in a duct with a 100 mm × 100 mm cross-section within a 265 L closed-loop chamber system (Supplementary Table 2).

Regarding power distribution and uneven desorption, the proposed system addresses these concerns through the following design features:

First, the modular cell-based architecture is designed for parallel electrical connection. As described in Eqs. 2 and 3, the total resistance of the filter module can be predicted for both series and parallel configurations. When cells are connected in parallel, each cell receives an equal voltage, ensuring uniform power delivery across the module regardless of the number of cells. This parallel configuration inherently mitigates the risk of uneven power distribution that would arise in a series arrangement.

Second, time-resolved thermal imaging was conducted on the carbon fiber bundle under applied voltages of 4-7 V (Supplementary Figs. 10 and 11). The results confirm that the temperature distribution along the fiber reaches a uniform steady-state within approximately 5 seconds, indicating that the high electrical conductivity of the carbon fiber (~12,000 filaments per roving) effectively minimizes Ohmic losses along the fiber length.

Third, regarding safety considerations, the operating voltage range of the system (DC 4-7 V) is well within the extra-low voltage (ELV) category (IEC 60449, ELV < 50 V AC / 120 V DC), which is inherently safe for occupied indoor environments. The low operating voltage, combined with the moderate desorption temperature (80-100 °C, below the thermal degradation threshold of 150 °C), ensures safe operation without risk of ignition or electrical hazard.

In response to the reviewer's comment, the typographical error has been corrected in the revised manuscript, and the structural parameters of the filter have been added to Supplementary Table 2. The thermal imaging results in Supplementary Figs. 10 and 11 document the temperature uniformity of the system.

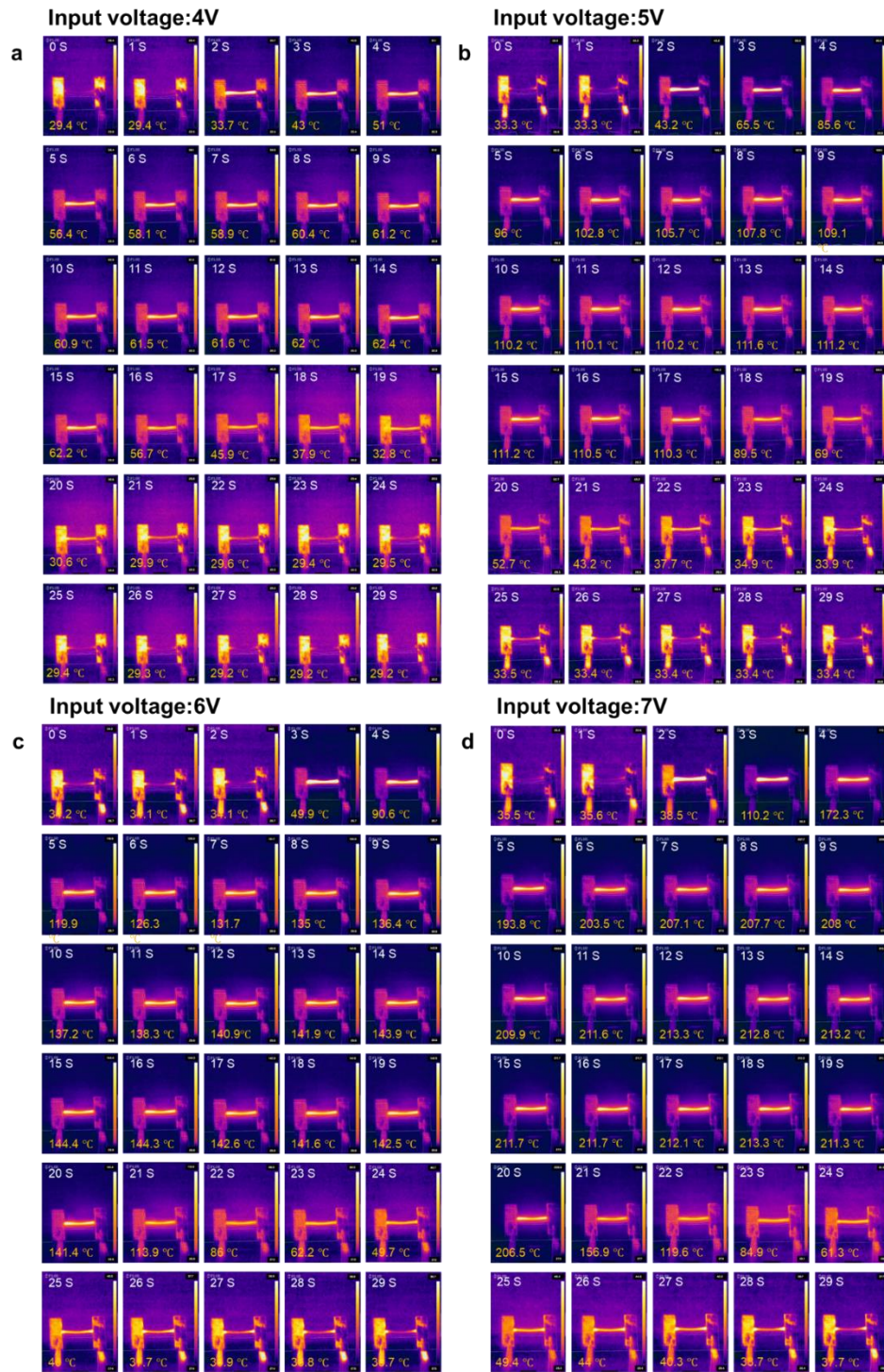
Before (Page 8):

Spray coating was applied one to four times on carbon fiber wound around a 10 mm × 10 mm acrylic plate.

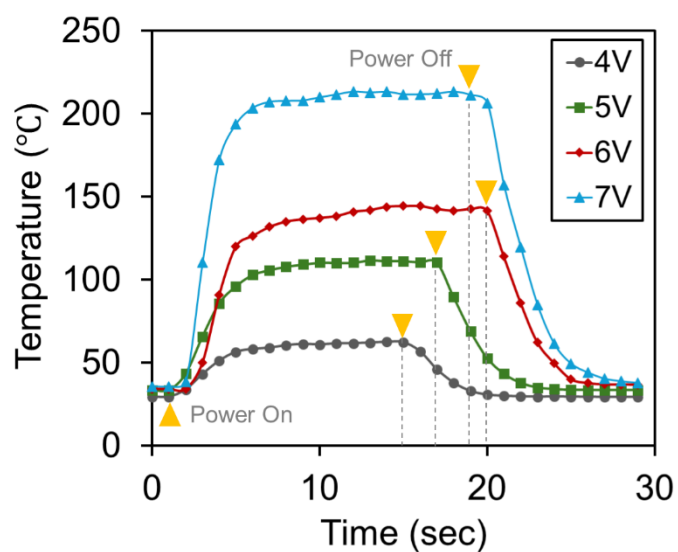
After (Page 8):

Spray coating was applied one to four times on carbon fiber wound around a 100 mm × 100 mm acrylic plate.

After:



Supplementary Fig. 10. Time-sequential thermal images of a carbon fiber bundle under applied voltages of (a) 4, (b) 5, (c) 6, and (d) 7 V.



Supplementary Fig. 11. Temperature–time curves of a carbon fiber bundle under applied voltages of 4, 5, 6, and 7 V.

Supplementary Table 2. Structural parameters of the CO₂ capture filter and experimental setup.

Parameter	Value
Number of cells	8
Fiber length per cell (cm)	53
Weight of the carbon fiber per length (g/cm)	4.13×10^{-3}
Weight of the coating per length (g/cm)	4.35×10^{-3}
Weight percent of the amine group (%)	50
Weight of the total coated amine group (g)	0.923
Volume of the experimental setup (L)	265
Scale of the acrylic chamber (cm × cm × cm)	50 × 50 × 50
Scale of the acrylic duct (cm × cm)	10 × 10
Diameter of the flexible ducts (cm)	13

6. Energy analysis shows that at high CO₂ targets (1,000 ppm) in summer, the CDCV system consumes 34% more energy than conventional DCV, which challenges the claim of overall energy savings.

Answer: We appreciate the reviewer's careful analysis and agree that this point warrants a clear explanation. The CDCV system differs from conventional DCV in that it incorporates a CO₂ capture filter to actively control indoor CO₂ concentration, and its energy efficiency is inherently dependent on the target CO₂ concentration set for operation. The energy analysis was conducted over a target concentration range of 600-1,000 ppm to identify the operational conditions under which the CDCV system demonstrates an energy saving advantage over conventional DCV.

As shown in Fig. 8(b), the energy consumed for filter regeneration in the CDCV system remains relatively constant regardless of the target CO₂ concentration, as it is governed by the combined effects of the sorbent's lab-scale capture capacity, regeneration efficiency, and sensible and latent heat contributions. Consequently, this tendency indicates that the CDCV system becomes more advantageous for reducing energy consumption as the target indoor CO₂ concentration decreases. The 34% increase in energy consumption observed at a target concentration of 1,000 ppm under summer conditions, as noted by the reviewer, is addressed in Figs. 8(d) and (e), where we explicitly discuss the underlying causes of this outcome and quantify the sorbent performance improvement required to achieve energy savings across all target concentration conditions.

We emphasize that the simulations presented in this study are based on experimentally measured sorbent performance from the lab-scale filter. Rather than overstating the system's current capabilities, we have taken the approach of defining the performance threshold that the sorbent must surpass in order for the CDCV system to deliver energy savings under all operating conditions. We hope this clarification adequately addresses the reviewer's concern.

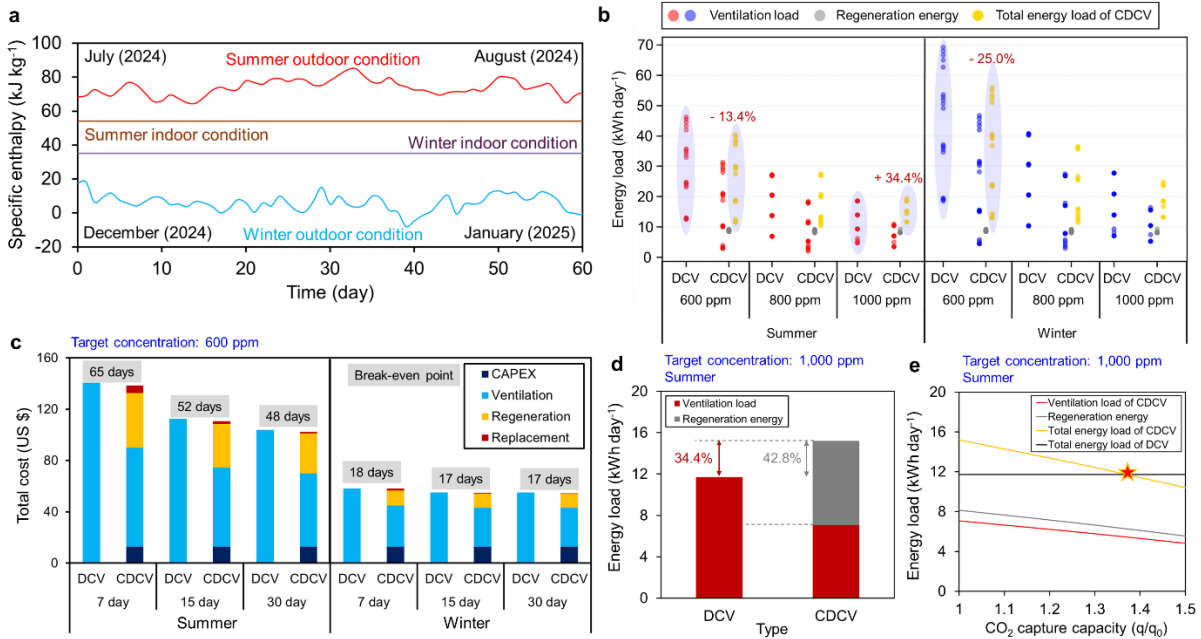


Fig. 8. Feasibility study comparing DCV and CDCV systems. (a) Seasonal variation of indoor/outdoor specific enthalpy under typical summer and winter conditions. **(b)** Comparison of total daily energy demand for DCV and CDCV systems. **(c)** Break-even point analysis based on filter replacement cycle. **(d)** Required reduction in regeneration energy to

achieve energy parity between CDCV and DCV systems. (e) Effect of increasing CO₂ capture capacity on the total energy load of CDCV system.

7. Proposed optimization strategies (increasing adsorption capacity) are theoretical and lack experimental validation, raising doubts about their feasibility.

Answer: We appreciate the reviewer's insightful comment. The reviewer raised a concern regarding the lack of experimental validation for the analysis presented in Fig. 8d and e, which we refer to as "energy optimization strategies." The system-scale scenario analysis was conducted by formulating the filter performance derived from lab-scale experiments into governing equations. Since the effectiveness of the system was evaluated based on the filter performance achieved in this study, its validity was confirmed only under the condition of maintaining 600 ppm. Therefore, to assess the conditions under which the CDCV system could achieve energy parity with the conventional system while maintaining a less "clean" indoor CO₂ target, a theoretical approach was considered the most appropriate path forward. Although this analysis is theoretical, we believe it holds value in that it can provide reference thresholds for the minimum electrothermal performance of Joule heating materials and the minimum required CO₂ capture capacity when other researchers try to apply a CO₂ capture filter in a specific indoor environment. While we acknowledge that experimentally validating the energy reduction performance across a wider range of operating conditions would be ideal, as suggested by the reviewer, a theoretical approach was considered the most appropriate method within the scope of the scenario analysis conducted in this study. We sincerely thank the reviewer for this constructive remark.

8. The deep learning model is trained entirely on simulated data, without validation against real occupancy or CO₂ measurements, limiting confidence in real-world performance.

Answer: The reviewer's concern is fully reasonable and is a point the authors have carefully considered. Recent research on indoor CO₂ capture can be broadly divided into two areas: the development of CO₂ capture materials, and the simulation or practical control of indoor CO₂ levels at the real-world scale. To bridge these two research domains, a preceding step is required: the proposal of a lab-scale solution that is applicable to indoor environments. In this study, we aimed to provide an integrative analysis spanning the full research scope by proposing a clearly defined application design in the form of a filter fabricated for indoor use, thereby advancing beyond what had previously remained at the material level without progressing toward actual indoor implementation. From this perspective, the core novelty of the present work lies in the development of the indoor-applicable filter and its lab-scale performance evaluation.

As the reviewer correctly points out, the simulated data applied in the deep learning component of this study does not fully reflect the actual CO₂ concentration dynamics observed in real indoor environments. In the simulation, factors such as CO₂ generation rate and ventilation rate were intentionally simplified in order to isolate and rigorously evaluate the filter performance derived from lab-scale experiments. We acknowledge that this represents a limitation of the present study, and that transitioning to real-world applications would necessitate building-scale experiments or the incorporation of more complex variable conditions. In accordance with the reviewer's suggestion, the limitations inherent in the simulation results have been explicitly stated in the manuscript and discussion sections.

Thank you for your valuable comment.

After (Page 27):

While the present study demonstrates a promising strategy for indoor CO₂ management, several limitations remain toward real-world adoption. The deep learning model was trained exclusively on simulated dataset, in which key parameters were intentionally simplified to isolate and evaluate the lab-scale filter performance, and has not been validated against real occupancy patterns or measured indoor CO₂ dynamics. The energy analysis and system-level simulation were also conducted under idealized boundary conditions, and system behavior under more complex and variable real-world scenarios remains to be verified. These findings underscore that bridging the gap between the current lab-scale framework and real-world adoption will require careful consideration of the following aspects. In addition to these analytical constraints, practical deployment will require confirmation that no harmful byproducts are generated during the Joule heating-based filter regeneration process. Additionally, oxidative degradation of amine functional groups under repeated thermal cycling in the presence of oxygen is a recognized challenge for long-term sorbent durability²³. In this study, the 200-cycle TGA test at 100 °C (Supplementary Fig. 3) showed that the overall sample mass decreased by only 2.36%, while the CO₂ capture capacity per unit mass remained stable with a slight increase of 2.28% from the first to the last cycle, and the moderate regeneration temperature (80–100 °C) is expected to substantially reduce the autoxidation rate compared to higher-temperature operations²⁴. However, since vacuum-assisted regeneration is impractical for indoor environments due to noise, the introduction of inert purge gas (e.g., Ar, N₂) during Joule heating may serve as a viable strategy to suppress oxygen exposure and mitigate oxidative aging. The long-term oxidative stability under extended real-world operation warrants further investigation. Furthermore, real-time responsive operation through Internet of Things (IoT)-based CO₂ monitoring is expected to be an essential component for dynamic, occupancy-adaptive control in actual building environments. Addressing these aspects in future work, namely building-scale validation, health safety assessment, and IoT-enabled control integration, would bring the realization of scalable indoor CO₂ capture within reach.

Before:

Discussion

In summary, this study presents a comprehensive framework for integrating CO₂ capture filter into demand-controlled ventilation (DCV) systems, addressing limitations of conventional indoor air quality management. At the material level, a regenerable amine-functionalized silica was developed and incorporated into a carbon fiber-based filter, enabling efficient thermal desorption via Joule heating. At the system level, a simulation platform assessed the performance of the CO₂ filter-integrated DCV (CDCV) system under varied occupancy and environmental conditions. Differential Evolution optimization identified key control parameters to minimize ventilation load while maintaining indoor CO₂ within acceptable limits. To enhance adaptability, a deep neural network was trained on large-scale simulation data for real-time control based on occupancy feedback. Case studies using real weather data demonstrated that the deep learning-assisted CDCV system achieved up to 28.3% energy savings compared to conventional ventilation. Feasibility analysis revealed two

critical pathways to achieve energy parity at high CO₂ setpoints: increasing sorbent adsorption capacity by 1.38 times or reducing regeneration energy by 42.8%. These results highlight the necessity of simultaneous advancements in sorbent material design and electric-to-thermal conversion efficiency. By linking material innovation with system-level implementation, this work provides a practical approach toward scalable, energy-efficient CO₂ capture in buildings

After (Page 28-29):

Discussion

In summary, this study presents a comprehensive framework for integrating CO₂ capture filter into demand-controlled ventilation (DCV) systems, addressing limitations of conventional indoor air quality management. At the material level, a regenerable amine-functionalized silica was developed and incorporated into a carbon fiber-based filter, enabling **localized** thermal desorption via Joule heating. At the system level, a simulation platform assessed the performance of the CO₂ filter-integrated DCV (CDCV) system under varied occupancy and environmental conditions. Differential Evolution optimization identified key control parameters to minimize ventilation load while maintaining indoor CO₂ within acceptable limits. To enhance adaptability, a deep neural network was trained on large-scale simulation data for real-time control based on occupancy feedback. Case studies using real weather data demonstrated that the deep learning-assisted CDCV system achieved up to 28.3% energy savings compared to conventional ventilation. Feasibility analysis revealed two critical pathways to achieve energy parity at high CO₂ setpoints: increasing sorbent adsorption capacity by 1.38 times or reducing regeneration energy by 42.8%. These results highlight the necessity of simultaneous advancements in sorbent material design and electric-to-thermal conversion efficiency. **Despite these promising outcomes, the present study has limitations in that the system-scale deep learning model was trained on simulated data without validation against real occupancy measurements, and the system-level analysis was conducted under simplified boundary conditions. Furthermore, the occupancy scenarios were constrained to 1–4 persons based on a typical residential setting, which may not fully capture the variability of other building types. The same analytical framework is, however, expected to be extendable to other occupancy conditions and building environments by adjusting the relevant input parameters. Future work incorporating building-scale experiments under real-world occupancy conditions, alongside safety validation of the regeneration process in occupied environments, will be essential to fully validate the proposed system toward real-world adoption. Nevertheless, by linking material innovation with system-level implementation, this work provides a meaningful step toward scalable CO₂ control in buildings. By linking material innovation with system level implementation, this work provides a practical approach toward scalable, energy efficient CO₂ capture in buildings.**

9. Key parameters (R_{occ} , R_{target}) are based on simulations, but their uncertainty or sensitivity is not discussed.

Answer: The variables mentioned by the reviewer, η_{des} , R_{occ} , and R_{target} , are calculated through a DE algorithm optimization based on input variable conditions, with constraints incorporated into the optimization process to ensure physical feasibility. Since the optimization algorithm yields identical output values under the same set of constraints, it is inherently difficult to perform conventional uncertainty and sensitivity analyses. Therefore, we conducted a case study across combinations of input variable conditions, applied machine learning to the resulting dataset, and evaluated the prediction accuracy of the FCDNN model, through which we performed a comprehensive analysis of sensitivity and prediction accuracy with respect to the input variable conditions. The results of this analysis are reflected in the main text and in Supplementary Note 4, Supplementary Table 4, and Supplementary Fig. 16. We hope this response adequately addresses the reviewer's concern. Thank you.

Page 22-23:

Deep learning-based indoor application case study

A predictive framework linking system inputs to optimal control parameters was developed using a FCDNN. The model was trained on optimized datasets to estimate η_{des} , R_{target} , and R_{occ} based on five key indoor variables. Bayesian optimization was applied to identify the optimal network architecture and hyperparameters, minimizing the combined MAE and RMSE. The trained model achieved normalized MAE values of 2.5%, 4.72%, and 3.81% for η_{des} , R_{target} , and R_{occ} , respectively (Supplementary Table 4). Scatter plots in Supplementary Fig. 16a, 16c, and 16e show strong agreement between predicted and actual values, demonstrating the model's ability to capture nonlinear relationships. Permutation-based feature importance analysis revealed that occupancy was the most influential factor for predicting R_{target} (26.72%) and η_{des} (12.75%), while adsorbent mass and C_{target} had significant effects on R_{occ} . Indoor volume showed minimal influence across all outputs. These findings are summarized in radar plots (Supplementary Fig. 16b, 16d, and 16f) and detailed in Supplementary Table 4, providing a comprehensive view of input feature impacts on model performance.

[Supplementary information](#)

Supplementary Note 4

System optimization methodology (Differential Optimization)

Following the development of the CO₂ capture filter and the integration of a dual-mode ventilation system, an optimization framework was established to maximize indoor air quality and energy efficiency. The key goal of this framework was to fine-tune the control parameters governing the dynamic transition between CO₂ adsorption (capture) and desorption (ventilation) phases. The optimization process focused on minimizing the deviation of indoor CO₂ concentration from a desired target value under predefined occupancy scenarios (1 to 4 persons) and fixed indoor volume settings (200-400 m³), with CO₂ generation calculated at 0.005 L s⁻¹ per person according to metabolic rate standards.

The key control parameters subject to optimization were:

- Desorption Efficiency ($\eta_{des.}$): The fraction of adsorbed CO₂ released during regeneration.
- Coefficient of per capita ventilation requirement (R_{occ}): The base ventilation requirement per occupant
- Ventilation sensitivity to CO₂ deviation (R_{target}): The proportionality constant for adjusting ACH in response to CO₂ deviations.

To solve this multi-parameter optimization problem, a Differential Evolution (DE) algorithm was employed. DE is a population-based global optimization method suited for nonlinear and non-differentiable objective functions²⁵. The algorithm iteratively evolves a population of candidate solutions using three key operations: mutation, crossover, and selection.

Mutation generates a donor vector from three randomly chosen distinct individuals $\vec{x}_{r1}, \vec{x}_{r2}, \vec{x}_{r3}$:

$$\vec{v}_i = \vec{x}_{r1} + F \cdot (\vec{x}_{r2} - \vec{x}_{r3}) \quad (S6)$$

where F is a mutation factor typically in the range 0.4 - 1.0.

Crossover constructs a trial vector ($\vec{u}_i$) by mixing components of the donor vector ($\vec{v}_i$) with the target vector ($\vec{x}_i$):

$$\vec{u}_i = v_{i,j} \text{ (if } rand_j \leq C_r \text{ or } j = j_{rand} \text{) or } x_{i,j} \text{ (otherwise)} \quad (S7)$$

C_r and $rand_j$ represent the crossover probability and a random number drawn from a uniform distribution in [0, 1], independently generated for each gene index j , respectively. $rand_j$ is compared to C_r to determine whether the donor or target vector contributes its value. To ensure that at least one parameter comes from the donor vector, a randomly selected index j_{rand} is always updated from $\vec{v}_i$.

Selection step evaluates the fitness of the trial vector ($\vec{u}_i$), against the original target $\vec{x}_i$:

$$\vec{x}_i^{new} = \vec{u}_i \text{ (if } f(\vec{u}_i) \leq f(\vec{x}_i) \text{) or } \vec{x}_i \text{ (otherwise)} \quad (S8)$$

Only individuals with improved or equal fitness replace their predecessors, ensuring gradual evolution toward the global optimum. The objective function minimized by DE was defined as the mean absolute deviation between the simulated CO₂ concentration and the target setpoint over a 24-hour period:

$$f(\vec{x}) = \frac{1}{T} \sum_{t=1}^T |C(t) - C_{target}| \quad \vec{x} = [\eta_{des.}, R_{occ}, R_{target}] \quad (S9)$$

To ensure meaningful and physically realistic optimization results, the control parameters were constrained within empirically and literature-supported bounds. The desorption efficiency $\eta_{des.}$, which defines the fraction of captured CO₂ released during regeneration, was limited to a range between 0.5 and 0.99. This ensures that the system avoids overly inefficient or idealized regeneration behaviors. R_{target} , which governs the degree to which ventilation rate increases in response to CO₂ deviation, was bounded between 0.0005 and 0.01 to avoid excessive or negligible ventilation responses. Lastly, the per capita ventilation rate R_{occ} was set between 3 and 10, in alignment with standard

ventilation requirements in indoor air quality literature and building design standards ²⁶. The simulation was run over 1440 timesteps (1-minute resolution for 24 hours), and each function evaluation accounted for varying occupancy patterns (1–4 persons), initial CO₂ levels, and indoor volumes. Within this framework, the DE algorithm was configured with the ‘best1bin’ mutation strategy, a maximum generation number of 10, and a fixed random seed (seed = 42) to ensure reproducibility. The population size was implicitly defined as 15 times the number of parameters (popsize × D), where D denotes the dimensionality of the parameter vector, resulting in 45 candidate solutions per generation. The crossover probability (C_r) was set to the default value of 0.7, and the mutation factor (F) was randomly selected in the range of 0.5 to 1.0 for each individual during evolution.

Upon convergence, the optimized parameters minimized concentration fluctuations while ensuring efficient regeneration. The system adaptively toggled between capture and ventilation modes based on the saturation state of the filter and real-time occupancy-driven CO₂ loads. This integrated simulation-optimization approach ensures practical applicability and energy-conscious operation in real-world indoor environments.

Fully connected deep neural network (FCDNN)

To enable real-time control, the regeneration efficiency ($\eta_{des.}$), ventilation rate coefficient (R_{occ}), and sensitivity coefficient (R_{target}) were modeled using a Fully Connected Deep Neural Network (FCDNN) ²⁷. The ReLU (Rectified Linear Unit) activation function was employed in all hidden layers to introduce non-linearity into the model while avoiding vanishing gradient issues. ReLU is computationally efficient and has been widely adopted in deep learning due to its ability to accelerate convergence during training ²⁸.

The computation process is detailed in Eq. S10–S15. The network comprises three hidden layers with ReLU activation functions.

$$x = [m_{filter}, Occupancy, V, C_{initial}, C_{target}] \quad (S10)$$

$$h_1 = ReLU(W_1x + b_1) \quad (S11)$$

$$h_2 = ReLU(W_2h_1 + b_2) \quad (S12)$$

$$h_3 = ReLU(W_3h_2 + b_3) \quad (S13)$$

$$h_4 = ReLU(W_3h_3 + b_4) \quad (S14)$$

$$y = W_4h_3 + b_4 = [\eta_{des.}, R_{occ}, R_{target}] \quad (S15)$$

The loss function was defined as the Mean Squared Error (MSE), as shown in Eq. S16, and model parameters were optimized using the Adam optimizer.

$$L_{MSE} = \frac{1}{N} \sum_i^N [(\eta_{des.} - \hat{\eta}_{des.})^2 + (R_{occ} - \hat{R}_{occ})^2 + (R_{target} - \hat{R}_{target})^2] \quad (S16)$$

The total dataset was split into training, validation, and test sets at a ratio of 7:2:1. All features were standardized using the mean and standard deviation of the training dataset.

Hyperparameter optimization (Bayesian optimization)

This study systematically identified the optimal architecture and training conditions for the FCDNN by employing Bayesian Optimization (BO), a probabilistic and sample-efficient method particularly suited for optimizing expensive black-box functions. BO constructs a surrogate model, commonly a Gaussian Process (GP), to approximate the objective function based on historical evaluations and then selects new candidates by maximizing an acquisition function such as Expected Improvement (EI). This strategy balances exploration of uncertain regions and exploitation of promising areas, thereby significantly reducing the number of evaluations required to converge to a high-performing configuration ²⁹.

In contrast to exhaustive grid search or random search methods, BO is particularly advantageous in high-dimensional or discrete-continuous mixed parameter spaces. It is capable of intelligently navigating the hyperparameter space using probabilistic performance modeling, which is especially beneficial for neural networks where each evaluation incurs substantial computational cost ³⁰. In this study, the application of BO allowed for automated, adaptive tuning of the FCDNN structure and training parameters without manual heuristics, thus enhancing model reproducibility and optimization transparency.

The optimization task in this study was formulated to minimize the combined validation error, defined as the sum of the mean absolute error (MAE) and the root mean squared error (RMSE), with respect to several hyperparameters. The batch size was selected from a discrete set of power-of-two values, while the learning rate was treated as a continuous variable defined over a log-scale range from 10^{-4} to 10^{-2} . The number of neurons in each hidden layer was constrained to commonly used values such as 16, 32, 64, and 128. In addition, the number of hidden layers was treated as a separate variable, allowing for configurations with two, three, or four layers, and the corresponding neuron parameters were conditionally applied depending on the selected network depth.

For example, when the number of layers was set to 2, only parameters related to the first two layers (h_1, h_2) were optimized; for configurations with 4 layers, h_1 to h_4 were included. Each structural setting had its own corresponding batch size and learning rate conditions to ensure fairness in evaluation. To handle these variations, the search space was dynamically defined using discrete indices mapped to valid choices for each architecture depth.

The objective function used for BO was formally expressed as Eq. S17

$$f(B, h_1, h_1, h_1, h_1, \eta, L) = -(MAE + RMSE) \quad (S17)$$

where B denotes batch size, h_i (for $i = 1$ to L) represents the number of neurons in the corresponding hidden layers, η is the learning rate, and $L \in (2,3,4)$ indicates the number of layers included in each trial. For consistent evaluation, dropout rate and training epochs were fixed across all configurations.

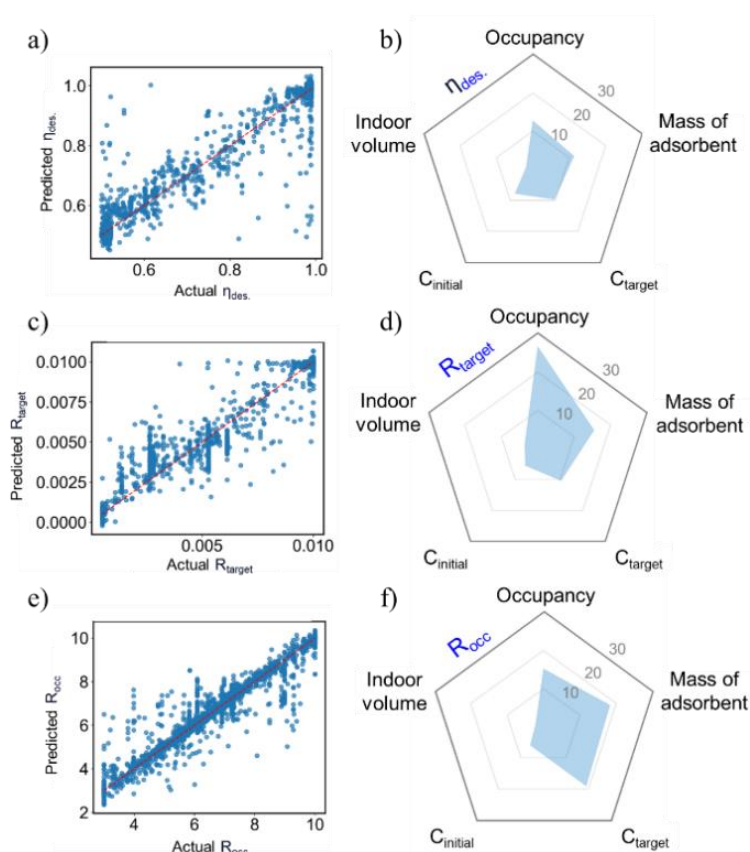
The BO implementation was performed using the existing Bayesian optimization library in Python program. It initiated with 5 random samples followed by 200 iterative updates. Discrete parameters were indexed and mapped back to their respective values during training, while continuous parameters were passed directly to the model. The use of BO under these constraints ensured efficient search over a mixed-variable space tailored to both structural and training hyperparameters. The search space of hyperparameters is denoted in

Supplementary Table 2.

Supplementary Table 4. Summary of DNN prediction accuracy and input variable importance for each output target.

Input variable	$\eta_{des.}$			R_{target}			R_{occ}		
	MAE (%)	MoA	Importance (%)	MAE (%)	MoA	Importance (%)	MAE (%)	MoA	Importance (%)
Mass of adsorbent			11.35			15.52			18.36
Occupancy			12.75			26.72			15.25
Indoor volume	2.50	0.85	1.77	4.72	0.0078	3.56	3.81	7.26	2.10
C_{target}			9.68			10.42			19.08
C_{init}			7.89			5.47			5.89

* MAE: Mean Absolute Error * MoA: Mean of Actual value



Supplementary Fig. 8. Comparison between predicted and actual values for three output variables (η_{des} , R_{target} , R_{occ}) using a deep neural network model (a, c, e), and corresponding permutation-based feature importance analysis visualized as radar plots (b, d, f).

10. Occupancy scenarios are limited to 1–4 people, which may not reflect the variability in real building environments, reducing generalizability.

Answer: We appreciate the reviewer's valuable comment. The sorbent application method proposed in this study is based on coating the sorbent onto carbon fiber. The occupancy setting of 1–4 persons was assumed based on a typical family residential space, considering a realistic applicable mass of the sorbent. In addition, fixing the boundary conditions is necessary, as it is difficult to derive optimal conditions without constraints. Just as assumptions are made to constrain the situation prior to conducting various analyses, the purpose of this study is to derive applicable solutions under specific scenarios by obtaining output values across various input variable conditions. As suggested by the reviewer, changing the occupancy setting would be expected to alter the optimal conditions, and it is anticipated that the same approach could be applied to derive results for other building types as well. In accordance with the reviewer's suggestion, a statement clarifying the scope of the occupancy conditions and the expandability of the proposed framework has been added to the manuscript. Thank you.

Before:

Fig. 6b presents the overall research framework for scenario-based indoor application studies, encompassing both optimization and deep learning phases. Five key indoor parameters—occupancy (1–4 persons), adsorbent mass (25–500 g), indoor volume (200–400 m³), target CO₂ concentration (600–1,200 ppm), and initial concentration (600–1,200 ppm)—were systematically varied to develop operational strategies that maintain the desired indoor CO₂ levels.

After (Page 18):

Fig. 6b presents the overall research framework for scenario-based indoor application studies, encompassing both optimization and deep learning phases. Five key indoor parameters—occupancy (1–4 persons), adsorbent mass (25–500 g), indoor volume (200–400 m³), target CO₂ concentration (600–1,200 ppm), and initial concentration (600–1,200 ppm)—were systematically varied to develop operational strategies that maintain the desired indoor CO₂ levels. **It should be noted that the occupancy was set to 1–4 persons based on a typical family residential space, and while this constrains the direct generalizability of the results, the proposed framework can be readily extended to other building types by adjusting the relevant input parameters.**

Before:

Discussion

In summary, this study presents a comprehensive framework for integrating CO₂ capture filter into demand-controlled ventilation (DCV) systems, addressing limitations of conventional indoor air quality management. At the material level, a regenerable amine-functionalized silica was developed and incorporated into a carbon fiber-based filter, enabling efficient thermal desorption via Joule heating. At the system level, a simulation platform assessed the performance of the CO₂ filter-integrated DCV (CDCV) system under varied

occupancy and environmental conditions. Differential Evolution optimization identified key control parameters to minimize ventilation load while maintaining indoor CO₂ within acceptable limits. To enhance adaptability, a deep neural network was trained on large-scale simulation data for real-time control based on occupancy feedback. Case studies using real weather data demonstrated that the deep learning-assisted CDCV system achieved up to 28.3% energy savings compared to conventional ventilation. Feasibility analysis revealed two critical pathways to achieve energy parity at high CO₂ setpoints: increasing sorbent adsorption capacity by 1.38 times or reducing regeneration energy by 42.8%. These results highlight the necessity of simultaneous advancements in sorbent material design and electric-to-thermal conversion efficiency. By linking material innovation with system-level implementation, this work provides a practical approach toward scalable, energy-efficient CO₂ capture in buildings

After (Page 28-29):

Discussion

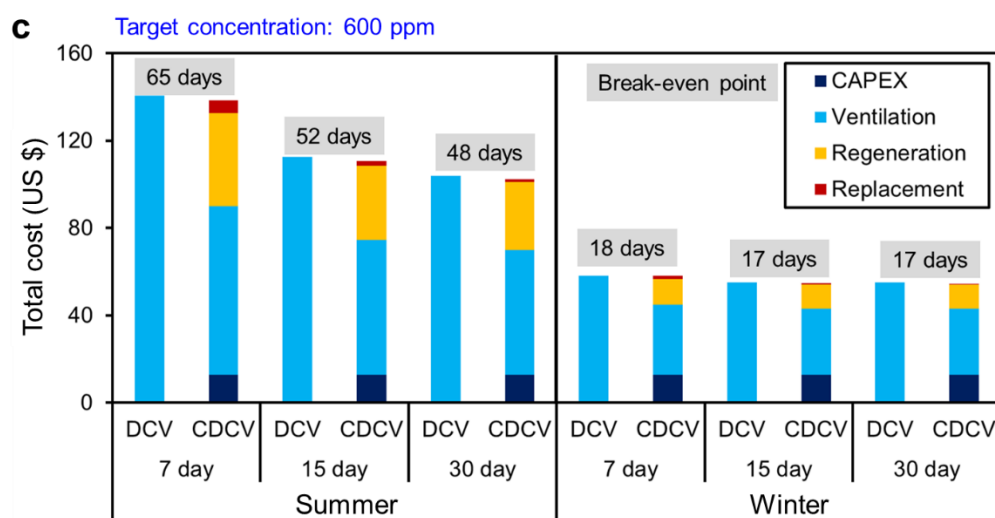
In summary, this study presents a comprehensive framework for integrating CO₂ capture filter into demand-controlled ventilation (DCV) systems, addressing limitations of conventional indoor air quality management. At the material level, a regenerable amine-functionalized silica was developed and incorporated into a carbon fiber-based filter, enabling **localized** thermal desorption via Joule heating. At the system level, a simulation platform assessed the performance of the CO₂ filter-integrated DCV (CDCV) system under varied occupancy and environmental conditions. Differential Evolution optimization identified key control parameters to minimize ventilation load while maintaining indoor CO₂ within acceptable limits. To enhance adaptability, a deep neural network was trained on large-scale simulation data for real-time control based on occupancy feedback. Case studies using real weather data demonstrated that the deep learning-assisted CDCV system achieved up to 28.3% energy savings compared to conventional ventilation. Feasibility analysis revealed two critical pathways to achieve energy parity at high CO₂ setpoints: increasing sorbent adsorption capacity by 1.38 times or reducing regeneration energy by 42.8%. These results highlight the necessity of simultaneous advancements in sorbent material design and electric-to-thermal conversion efficiency. **Despite these promising outcomes, the present study has limitations in that the system-scale deep learning model was trained on simulated data without validation against real occupancy measurements, and the system-level analysis was conducted under simplified boundary conditions. Furthermore, the occupancy scenarios were constrained to 1–4 persons based on a typical residential setting, which may not fully capture the variability of other building types. The same analytical framework is, however, expected to be extendable to other occupancy conditions and building environments by adjusting the relevant input parameters. Future work incorporating building-scale experiments under real-world occupancy conditions, alongside safety validation of the regeneration process in occupied environments, will be essential to fully validate the proposed system toward real-world adoption. Nevertheless, by linking material innovation with system-level implementation, this work provides a meaningful step toward scalable CO₂ control in buildings.** ~~By linking material innovation with system-level implementation, this work provides a practical approach toward scalable, energy-efficient CO₂ capture in buildings~~

11. No detailed cost analysis is provided. The high cost of carbon fiber and Joule heating infrastructure could offset energy savings.

Answer: We thank the reviewer for highlighting the need for an economic feasibility evaluation. Based on the costs of the carbon fiber and materials utilized in this study, we performed a break-even point analysis for the 600 ppm concentration maintenance condition presented in Fig. 9b. The economic analysis has been added to the manuscript along with the corresponding figure, and the detailed analytical methodology has also been included in the Supplementary Information as Supplementary Note 7. Thank you.

After (Page 25):

A techno-economic assessment (TEA) was conducted to evaluate the practical feasibility of the CDCV system by comparing the total daily cost against that of the conventional DCV system across summer and winter conditions and three filter replacement intervals (7, 15, and 30 days) (Fig. 9c). The total cost of the CDCV system was decomposed into four components: capital expenditure (CAPEX) for system installation, ventilation energy cost, Joule-heating regeneration electricity cost, and periodic consumable replacement cost, whereas the DCV system incurred only ventilation-related energy costs (detailed methodology and material costs are provided in Supplementary Note 7 and Supplementary Table 5). As shown in Fig. 9, despite the additional CAPEX and operational costs associated with CO₂ capture and regeneration, the CDCV system achieved a lower cumulative total cost than the DCV system beyond a break-even point in all evaluated scenarios. In summer conditions, the break-even point ranged from 65 days (7-day replacement interval) to 48 days (30-day replacement interval). In winter, the break-even point was markedly shorter, falling within only 17–18 days across all replacement intervals. This pronounced seasonal difference arises because the ventilation thermal load is substantially larger in winter due to the greater temperature differential between indoor and outdoor air, which amplifies the magnitude of ventilation energy savings achievable by the CDCV system and thereby accelerates cost recovery. These results demonstrate that the CDCV system can recover its initial investment within a practically short operational period and deliver sustained cost benefits over time, with the economic advantage being particularly pronounced under cold-climate conditions.



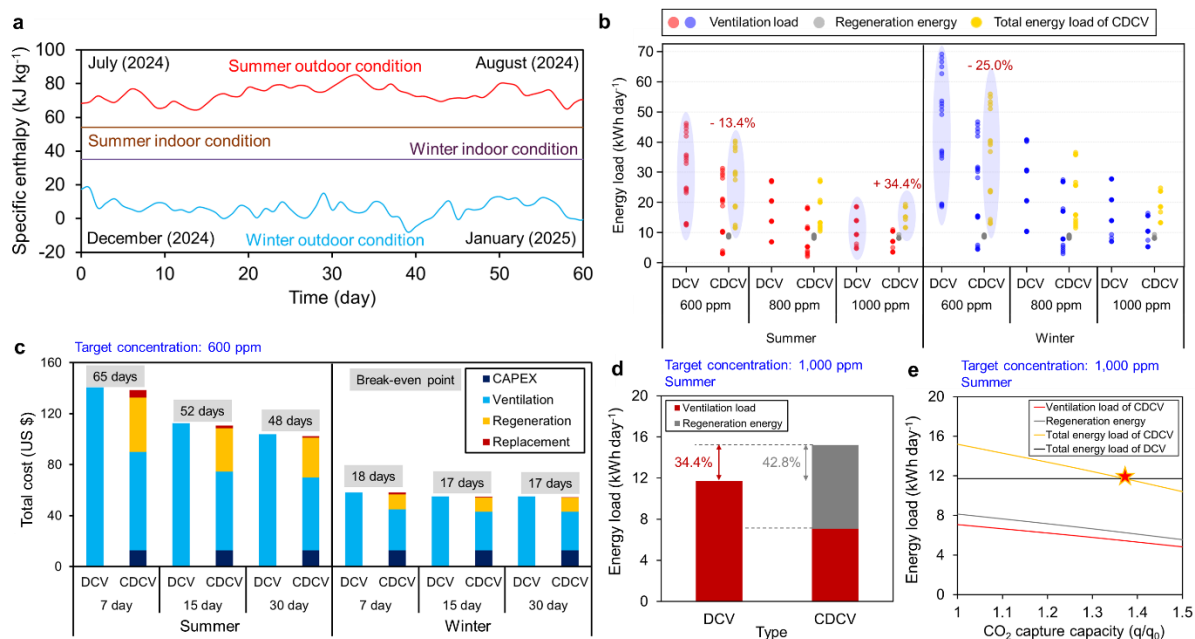


Fig. 9. Feasibility study comparing DCV and CDCV systems. (a) Seasonal variation of indoor/outdoor specific enthalpy under typical summer and winter conditions. **(b)** Comparison of total daily energy demand for DCV and CDCV systems. **(c) Break-even point analysis based on filter replacement cycle. (d)** Required reduction in regeneration energy to achieve energy parity between CDCV and DCV systems. **(e)** Effect of increasing CO₂ capture capacity on the total energy load of CDCV system.

Supplementary information

Supplementary Note 7

Techno-economic assessment

The techno-economic assessment was conducted to quantify the economic feasibility of the proposed CDCV system relative to a conventional DCV system. The analysis considered the additional cost associated with filter fabrication, regeneration electricity consumption, and periodic replacement, together with the economic benefit obtained from reducing ventilation-related energy demand. Since the system performance in this study was evaluated on a daily basis, the economic analysis was also formulated using daily energy consumption and daily operating cost as the basic units.

The system boundary for energy demand calculation was defined at the ventilation unit level, with the conventional DCV system taken as the reference case and the proposed CDCV system taken as the target case. Only the components and energy terms directly affected by integration of the CO₂ capture filter were included in the economic assessment. Under this definition, the reference DCV system was assumed to incur only the ventilation-related thermal conditioning load associated with the introduction of outdoor air, whereas the CDCV system incurred both the reduced ventilation load and the electrical energy required for Joule-heating regeneration of the filter.

The total cost of the CDCV system was divided into initial capital expenditure

(CAPEX) and daily operating expenditure (OPEX). The initial capital expenditure of the CDCV system was defined as a one-time investment required for system installation. This cost includes the housing structure, copper electrodes, electrical wiring, and assembly and installation components necessary to operate the Joule-heating filter module:

$$\text{CAPEX}_{\text{CDCV}} = C_{\text{housing}} + C_{\text{wire}} + C_{\text{copper}} \cdot N_{\text{cell}} + C_{\text{install}} \quad (\text{S24})$$

where N_{cell} is the total number of cells. The installation cost of the filter was assumed to be 20% of the direct equipment cost. Components were assumed to remain intact over the system lifetime and were therefore not subject to periodic replacement.

In contrast, the functional materials responsible for CO₂ capture and regeneration were treated as consumable components and included in OPEX. These materials consist of carbon fiber, amine (PEI), silica, and IPA, which form the active adsorption and coating layer of the filter. Accordingly, the replacement cost was defined based on the periodic interval of these consumable materials.

$$\text{OPEX}_{\text{CDCV,replace}} = (C_{\text{carbon fiber}} + C_{\text{PEI}} + C_{\text{silica}} + C_{\text{IPA}}) \cdot N_{\text{cell}} \quad (\text{S25})$$

Assuming a fixed replacement interval, the replacement cost was converted into an equivalent daily maintenance cost to ensure consistency with the day-based energy analysis. The daily replacement cost was therefore expressed as

$$\text{OPEX}_{\text{CDCV,replace,day}} = \text{OPEX}_{\text{CDCV,replace}} / N_{\text{interval}} \quad (\text{S26})$$

where N_{interval} is the replacement interval expressed in days.

In addition to the replacement cost, the operating expenditure of the CDCV system includes the electricity cost associated with Joule-heating regeneration. The daily regeneration energy consumption obtained from the system simulation was converted into a daily electricity cost using the applicable electricity tariff:

$$\text{OPEX}_{\text{CDCV,regen,day}} = E_{\text{regen,day}} \cdot P_{\text{elec}} \quad (\text{S27})$$

where $E_{\text{regen,day}}$ is the daily regeneration energy consumption and P_{elec} is the unit electricity price. Accordingly, the total daily operating expenditure of the CDCV system was defined as the sum of ventilation energy load, regeneration electricity cost and daily replacement cost:

$$\text{OPEX}_{\text{CDCV,day}} = E_{\text{CDCV,day}} \cdot P_{\text{elec}} + \text{OPEX}_{\text{CDCV,regen,day}} + \text{OPEX}_{\text{CDCV,replace,day}} \quad (\text{S28})$$

For the reference DCV system, the daily operating expenditure consists only of the ventilation-related energy cost, which was calculated from the daily ventilation energy demand:

$$\text{OPEX}_{\text{DCV,day}} = E_{\text{DCV,day}} \cdot P_{\text{elec}} \quad (\text{S29})$$

The economic performance of the CDCV system can be evaluated based on the balance between the reduced ventilation energy cost and the additional costs associated with filter regeneration and material replacement. Thus, the daily net cost saving (CS) achieved by the CDCV system was defined as the difference between the operating expenditures of the reference and proposed systems:

$$CS_{\text{day}} = OPEX_{\text{DCV,day}} - OPEX_{\text{CDCV,day}} \quad (\text{S30})$$

which represents the net economic benefit obtained from reducing ventilation energy demand while accounting for regeneration and replacement costs. Furthermore, the simple payback period was then calculated by comparing the initial investment for proposed system with the daily net cost saving:

$$\text{Payback period} = \frac{CAPEX_{\text{CDCV}}}{CS_{\text{day}}} \quad (\text{S31})$$

This metric indicates the time required for the cumulative operating cost savings to recover the additional capital investment associated with the CDCV system.

Supplementary Table 5. Raw materials and unit prices used for fabrication of the CDCV filter module.

Material	Unit	Price (\$)	Supplier
Carbon fiber	5,000 m	147	Fiberman
Polyethylenimine (PEI 600)	1 L	121	Sigma Aldrich
Silica nanopowder (60–70 nm)	1 kg	440	Koreanano
Copper rod (Φ5 mm)	1 m	1.5	-
Electrical wire	1 m	0.3	-
Isopropyl alcohol (IPA)	4 L	16	Sigma Aldrich
Module housing(20 cm × 20 cm)	1 ea	6.5	-

12. The manuscript mentions “modular scaling,” but no intermediate-scale prototype is demonstrated to support feasibility beyond lab experiments.

Answer: The term “modular scaling” in this study refers to the ability to adjust the filter capacity by stacking multiple identical unit cells in a modular configuration, rather than scaling a single monolithic structure. This design allows direct scalability without requiring intermediate-scale prototypes, as the overall system performance can be predicted from the behavior of individual cells and their electrical configuration (series or parallel), as described in Eqs. (2) and (3). Therefore, additional intermediate-scale experiments were not considered essential for validating the scalability concept in this work. To clarify this point, a statement explicitly describing the modular scalability concept has been added to the electro-thermal characteristics section of the revised manuscript.

After (Page 9):

For scaled-up module design, total resistance can be predicted based on the system’s

electrical composition; series or parallel, using Eqs. 2 and 3. Here, m represents the number of modules per filter unit. **This modular architecture enables capacity adjustment by stacking multiple identical unit cells rather than scaling a single monolithic structure, allowing the overall system performance to be predicted directly from the behavior of individual cells and their electrical configuration without requiring intermediate-scale prototyping.** While electrical power was estimated from voltage and current measurements, the observed temperature did not correlate directly with input power (Fig. 4d). This discrepancy is attributed to the structural complexity of the carbon fiber bundle, comprising ~12,000 filaments (~6 μm diameter each), which affects heat distribution.

13. Some experimental details, such as airflow velocity, pressure drop, and sensor accuracy, are not fully specified.

Answer: The fan specifications and sensor accuracy used in the lab-scale experimental apparatus are documented in Supplementary Table 1 of the Supplementary Information. Regarding the pressure drop mentioned by the reviewer, the filter geometry in the actual experimental setup was designed so as not to significantly obstruct the flow path, making it difficult to obtain meaningful pressure drop measurements from the sensors. Therefore, in order to address the reviewer's request, a CFD analysis was conducted to evaluate the pressure drop across the filter, and the corresponding results have been added to the Supplementary Information. We hope this response adequately meets the reviewer's request.

Supporting information

Supplementary Table 1. Specification of the CO₂ sensor, fan, mass flow controller, and power supply for evaluation of CO₂ concentration, temperature, and relative humidity.

			Type	Range	Error	Resolution	Response
CO ₂ & RH sensor (HT 2000)	CO ₂		0-9999 ppm	± 50 ppm	-	10 s	
	Temperature		-10 – 70 °C	± 1.2 °C	0.1 °C	-	
	Relative humidity		0.1 – 99.9%	± 3%	0.1%	-	
Fan			Voltage	Air flow	Speed	Dimensions	
(NMB11938MB)			220 VAC	172 CMH	2900 RPM	119 mm × 38 mm × 119 mm	
Mass flow controller			Range	Accuracy	Repeatability	Response time	
(WIZ-701)			1000 sccm	± 1.0%	± 0.3%	≤1sec	
Power supply			Voltage range	Load regulation	Current Range		Load regulation

(MK-6005D)	(voltage)		(current)
	0-60 V	≤0.01% 0-5 A	≤0.1%

Before:

Breakthrough adsorption test is widely employed to evaluate the performance of CO₂ adsorbents at the lab-scale and serves as a standard performance metric. However, its applicability to actual ventilation systems is limited due to the high pressure drop, since these systems already incorporate pressure-inducing components such as **High Efficiency Particulate Air (HEPA)** filters and heat exchangers. In this study, the performance of the carbon fiber CO₂ capture filter was assessed using a batch-type acrylic chamber setup (Fig. 4a), which facilitates internal air circulation, continuous monitoring of CO₂ concentration, and simulates filter placement in realistic ventilation environments. Detailed equipment specifications are provided in Supplementary Table 1.

After (Page 12):

Breakthrough adsorption test is widely employed to evaluate the performance of CO₂ adsorbents at the lab-scale and serves as a standard performance metric. However, its applicability to actual ventilation systems is limited due to the high pressure drop, since these systems already incorporate pressure-inducing components such as **High Efficiency Particulate Air (HEPA)** filters and heat exchangers. In this study, the performance of the carbon fiber CO₂ capture filter was assessed using a batch-type acrylic chamber setup (Fig. 5a), which facilitates internal air circulation, continuous monitoring of CO₂ concentration, and simulates filter placement in realistic ventilation environments. Detailed equipment specifications and **the structural parameters of the CO₂ capture filter** are provided in Supplementary Table 1 and Supplementary Table 2. **Since direct differential pressure measurement across the filter was not feasible in the lab-scale apparatus, CFD simulations were conducted to characterize the pressure drop. The detailed methodology and boundary conditions are provided in Supplementary Note 1, and the corresponding pressure contour results are shown in Supplementary Fig. 12. The simulated differential pressure ranged from 0.393 Pa (3 cells, 1 m s⁻¹) to 14.144 Pa (9 cells, 3 m s⁻¹). These values represent less than 3.4% variation in fan power demand, which was considered negligible and therefore excluded from the energy calculations.**

Supporting information

Supplementary Note 1

Direct differential pressure measurement across the CO₂ capture filter was not feasible in the lab-scale apparatus. To address this, steady-state CFD simulations were performed using ANSYS Fluent to characterize the pressure drop under representative operating conditions. The computational domain consisted of a rectangular duct with a cross-sectional area of 100 mm × 100 mm. Copper rods with a diameter of 5 mm were placed at the inlet and outlet faces of the filter section to replicate the cell geometry, with cell numbers of 3, 5, 7, and 9. The winding geometry of the carbon fiber was excluded from the domain to simplify the model

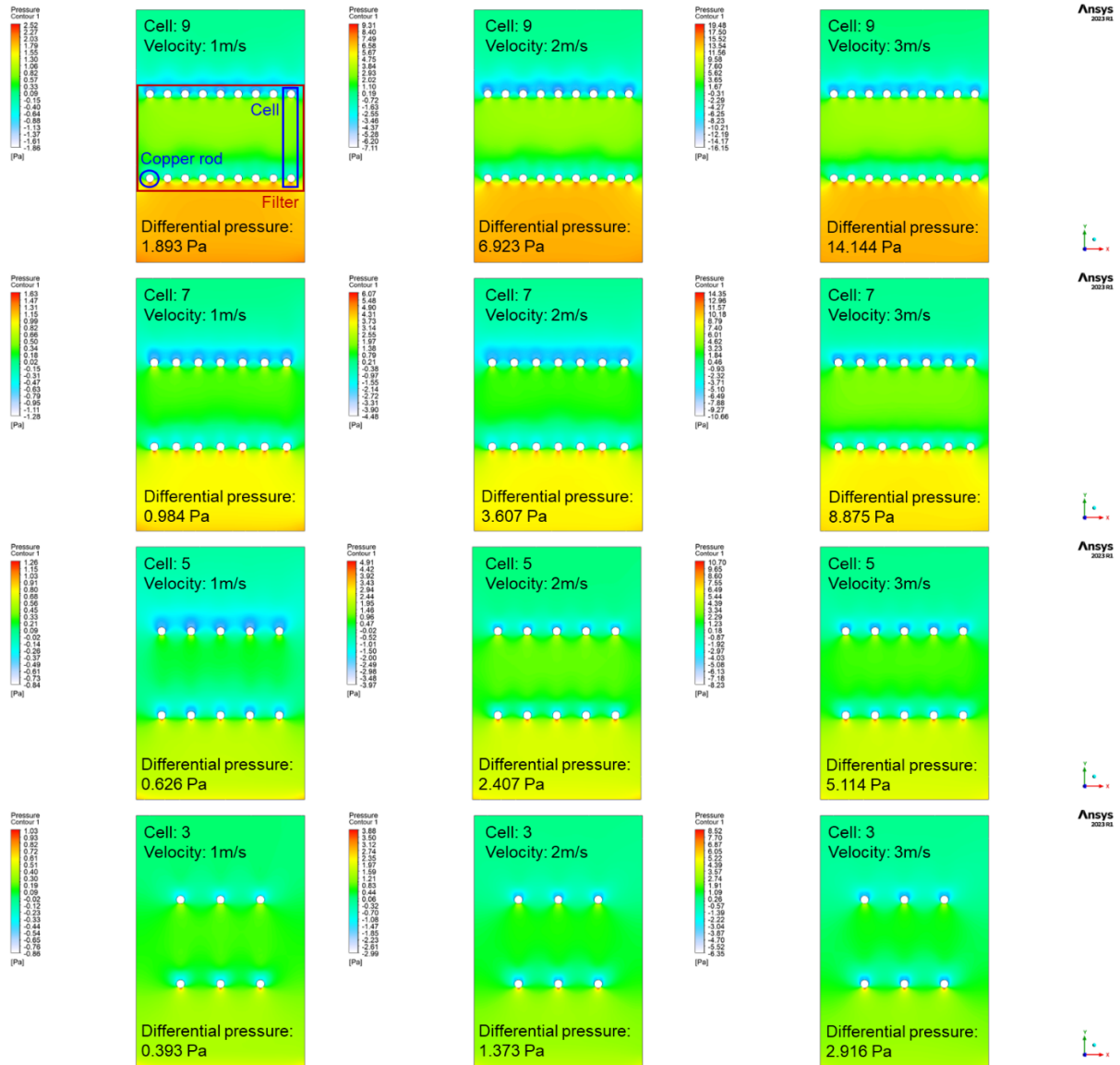
while preserving the essential flow-blocking characteristics of the filter structure. Inlet velocities of 1, 2, and 3 m s⁻¹ were applied as boundary conditions, and the differential pressure was defined as the area-averaged static pressure difference between the filter inlet and outlet planes.

The governing equations solved in the simulations are the continuity and momentum equations as follows:

$$\frac{\partial}{\partial t}(\rho) + \nabla \cdot (\rho \vec{u}) = 0 \quad (S1)$$

$$\frac{\partial}{\partial t}(\rho \vec{u}) + \nabla \cdot (\rho \vec{u} \vec{u}) = -\nabla P + \nabla \cdot (\mu(\nabla \vec{u} + \nabla \vec{u}^T)) + \rho \vec{g} \quad (S2)$$

Turbulence was modeled using the realizable k-ε model with enhanced wall functions. Pressure-velocity coupling was handled via the SIMPLE algorithm, and spatial discretization employed second-order upwind schemes for both momentum and pressure.



Supplementary Fig. 12. CFD-simulated pressure contours and differential pressure across the CO₂ capture filter under varying cell numbers and inlet air velocities.

14. Comparisons with alternative low-energy CO₂ capture strategies (e.g., MOFs, liquid scrubbers) are missing.

Answer: We thank the reviewer for this suggestion. While a full comparative analysis across all CO₂ capture strategies is beyond the scope of this study, we have addressed this comment by providing contextual positioning of the proposed system relative to alternative low-energy capture strategies.

Liquid scrubbers

In the conventional CO₂ capture process using aqueous monoethanolamine (MEA) solutions, amine regeneration is performed at temperatures of 120-140 °C¹⁰. Moreover, because the water-based MEA solution possesses high specific and latent heat capacity, the regeneration process above 100 °C consumes substantial thermal energy³¹, with reported reboiler duties in the range of approximately 3.8-4.2 GJ t⁻¹CO₂¹¹. In addition, the process requires substantial infrastructure including absorber, stripper columns, solvent circulation pumps, and heat exchangers. More critically, amine scrubbing processes are known to emit volatile degradation products including ammonia, aldehydes, and potentially carcinogenic nitrosamines during thermal cycling, which pose health risks to building occupants¹². These characteristics make liquid scrubbing impractical for building-scale indoor CO₂ management applications.

Metal-organic frameworks (MOFs)

As noted in the Introduction, MOFs have attracted considerable interest for CO₂ capture due to their tunable pore structures and high surface areas. However, their CO₂ adsorption performance is significantly reduced under humid conditions¹³, and their synthesis processes remain more complex and costly compared to commercially available amine functionalized silica materials¹⁴.

Zeolites and other physisorbents

Zeolite-based sorbents offer high selectivity but typically require regeneration temperatures of 150-250 °C¹⁵ and exhibit significant capacity reduction under humid conditions, with reported decreases of up to 93% at 74% relative humidity for zeolite 13X¹⁶.

The sorbent system proposed in this study was specifically designed to address the practical requirements of indoor deployment, low regeneration temperature (80-100 °C), CO₂ selectivity, humidity tolerance, low material cost, and compatibility with existing ventilation infrastructure.

After:

Supplementary Note 8. Comparison with existing electrothermal CO₂ capture systems

It is also worth noting that alternative CO₂ capture strategies were considered but deemed unsuitable for the intended indoor application. Liquid amine scrubbing (e.g., aqueous MEA solutions) requires regeneration temperatures of 120-140 °C¹⁰ with reboiler duties of 3.8-4.2 GJ t⁻¹CO₂¹¹, and is known to emit volatile degradation products including ammonia, aldehydes, and potentially carcinogenic nitrosamines during thermal cycling¹², posing unacceptable health risks in enclosed indoor spaces where stack-based atmospheric dispersion is unavailable. Metal-organic frameworks, while offering high surface areas and

tunable pore structures, suffer from significant capacity reduction under humid conditions¹³ and involve more complex and costly synthesis processes compared to commercially available amine-functionalized silica¹⁴. Zeolite-based physisorbents typically require regeneration temperatures of 150-250 °C¹⁵ and exhibit up to 93% capacity loss at 74% relative humidity¹⁶, making them incompatible with the moderate-temperature, humidity-tolerant operation required for indoor environments.

15. Terms like “efficient” and “practical” are used without quantitative support; the language could be more precise.

Answer: We appreciate the reviewer's comment regarding the use of imprecise terminology. As pointed out, we agree that the use of ambiguous terms such as "efficient" and "practical" should be avoided in contexts where quantitative justification is not provided. Accordingly, these expressions have been replaced with more precise alternatives or removed throughout the manuscript to eliminate unsubstantiated language. Thank you.

Before:

This work demonstrates a **practical** pathway to implementation, establishing both the material's effectiveness and the feasibility of integrating such filters into existing building ventilation systems.

After (Page 3):

This work demonstrates a viable implementation pathway, validated through material characterization, lab-scale test, and system-level energy analysis.

Before:

These structured formats aim to facilitate faster mass transfer and reduce pressure drop, thereby enhancing **practical** applicability.

After (Page 3):

These structured formats aim to facilitate faster mass transfer and reduce pressure drop. ~~thereby enhancing **practical** applicability.~~

Before:

In contrast, Joule heating enables localized, conductive heat transfer within the adsorbent itself, achieving more targeted and energy-**efficient** thermal regeneration.

After (Page 3):

In contrast, Joule heating enables localized, conductive heat transfer within the adsorbent itself, minimizing heat losses associated with convective heating approaches.

Before:

By combining material-level analysis, lab-scale filter fabrication, and scenario based indoor CO₂ reduction modeling, this work offers a **practical** pathway toward bridging the gap between sorbent innovation and real-world deployment in building ventilation systems.

After (Page 4):

By integrating material-level analysis, lab-scale filter fabrication, and scenario-based indoor CO₂ reduction modeling, this work serves as a roadmap for evaluating the feasibility and practical validity of applying solid sorbents to building ventilation systems.

Before:

These results demonstrate the system's capability for stable operation under realistic indoor environments without significant alteration of temperature or humidity, underscoring its **practical** applicability.

After (Page 14):

These results demonstrate the system's capability for stable operation under realistic indoor environments without significant alteration of temperature or humidity. ~~underscoring its~~ **practical** applicability.

Before:

These results demonstrate that the deep learning-based approach offers a more adaptive and energy-**efficient** strategy for maintaining indoor CO₂ stability under dynamic conditions.

After (Page 22):

These results demonstrate that the deep learning-based approach offers a more adaptive and **responsive control** strategy for maintaining indoor CO₂ stability under dynamic **occupancy** conditions.

Before:

At the material level, a regenerable amine-functionalized silica was developed and incorporated into a carbon fiber-based filter, enabling **efficient** thermal desorption via Joule heating.

After (Page 28):

At the material level, a regenerable amine-functionalized silica was developed and incorporated into a carbon fiber-based filter, enabling **localized** thermal desorption via Joule heating.

16. The Discussion and Conclusion could include a more critical reflection on limitations and potential barriers to real-world adoption.

Answer: As noted in Comments 8 and 10, the system-level analysis presented in this study has some limitations making it difficult to directly guarantee real-world performance. The generalization of lab-scale filter performance and the simplification of variable conditions at the system scale mean that the results may deviate from trends observed in actual building environments. However, as communicated to the reviewer in the preceding responses, prior studies in this field have remained confined either to material-level research on low-concentration CO₂ capture or to system-level measurements and simulations, with no bridging solution linking the two fields. In this study, we propose a filter design that enables localized heating while minimizing pressure drop, with a stackable architecture that allows capacity to be adjusted to target demands, thereby offering a directional framework for evaluating the system-level applicability of CO₂ capture materials.

Beyond the limitations addressed in Comments 8 and 10, additional considerations remain for practical real-world adoption. First, the potential generation of byproducts during the filter regeneration process that may affect occupant health should be assessed prior to deployment in occupied spaces. Second, real-time responsive operation based on continuous CO₂ monitoring via Internet of Things (IoT) integration is expected to be a necessary component for practical implementation, enabling dynamic control aligned with actual indoor CO₂ fluctuations. These aspects are also added in the manuscript as important directions for future work. Thank you.

After (Page 27):

While the present study demonstrates a promising strategy for indoor CO₂ management, several limitations remain toward real-world adoption. The deep learning model was trained exclusively on simulated dataset, in which key parameters were intentionally simplified to isolate and evaluate the lab-scale filter performance, and has not been validated against real occupancy patterns or measured indoor CO₂ dynamics. The energy analysis and system-level simulation were also conducted under idealized boundary conditions, and system behavior under more complex and variable real-world scenarios remains to be verified. These findings underscore that bridging the gap between the current lab-scale framework and real-world adoption will require careful consideration of the following aspects. In addition to these analytical constraints, practical deployment will require confirmation that no harmful byproducts are generated during the Joule heating-based filter regeneration process. Additionally, oxidative degradation of amine functional groups under repeated thermal cycling in the presence of oxygen is a recognized challenge for long-term sorbent durability²³. In this study, the 200-cycle TGA test at 100 °C (Supplementary Fig. 3) showed that the overall sample mass decreased by only 2.36%, while the CO₂ capture capacity per unit mass remained stable with a slight increase of 2.28% from the first to the last cycle, and the moderate regeneration temperature (80–100 °C) is expected to substantially reduce the autoxidation rate compared to higher-temperature operations²⁴. However, since vacuum-assisted regeneration is impractical for indoor environments due to noise, the introduction of inert purge gas (e.g., Ar, N₂) during Joule heating may serve as a viable strategy to suppress oxygen exposure and mitigate oxidative aging. The long-term oxidative stability under extended real-world operation warrants further investigation. Furthermore, real-time responsive operation through Internet of Things (IoT)-based CO₂

monitoring is expected to be an essential component for dynamic, occupancy-adaptive control in actual building environments. Addressing these aspects in future work, namely building-scale validation, health safety assessment, and IoT-enabled control integration, would bring the realization of scalable indoor CO₂ capture within reach.

Before:

In summary, this study presents a comprehensive framework for integrating CO₂ capture filter into demand-controlled ventilation (DCV) systems, addressing limitations of conventional indoor air quality management. At the material level, a regenerable amine-functionalized silica was developed and incorporated into a carbon fiber-based filter, enabling efficient thermal desorption via Joule heating. At the system level, a simulation platform assessed the performance of the CO₂ filter-integrated DCV (CDCV) system under varied occupancy and environmental conditions. Differential Evolution optimization identified key control parameters to minimize ventilation load while maintaining indoor CO₂ within acceptable limits. To enhance adaptability, a deep neural network was trained on large-scale simulation data for real-time control based on occupancy feedback. Case studies using real weather data demonstrated that the deep learning-assisted CDCV system achieved up to 28.3% energy savings compared to conventional ventilation. Feasibility analysis revealed two critical pathways to achieve energy parity at high CO₂ setpoints: increasing sorbent adsorption capacity by 1.38 times or reducing regeneration energy by 42.8%. These results highlight the necessity of simultaneous advancements in sorbent material design and electric-to-thermal conversion efficiency. By linking material innovation with system-level implementation, this work provides a practical approach toward scalable, energy-efficient CO₂ capture in buildings

After (Page 28-29):

Discussion

In summary, this study presents a comprehensive framework for integrating CO₂ capture filter into demand-controlled ventilation (DCV) systems, addressing limitations of conventional indoor air quality management. At the material level, a regenerable amine-functionalized silica was developed and incorporated into a carbon fiber-based filter, enabling **localized** thermal desorption via Joule heating. At the system level, a simulation platform assessed the performance of the CO₂ filter-integrated DCV (CDCV) system under varied occupancy and environmental conditions. Differential Evolution optimization identified key control parameters to minimize ventilation load while maintaining indoor CO₂ within acceptable limits. To enhance adaptability, a deep neural network was trained on large-scale simulation data for real-time control based on occupancy feedback. Case studies using real weather data demonstrated that the deep learning-assisted CDCV system achieved up to 28.3% energy savings compared to conventional ventilation. Feasibility analysis revealed two critical pathways to achieve energy parity at high CO₂ setpoints: increasing sorbent adsorption capacity by 1.38 times or reducing regeneration energy by 42.8%. These results highlight the necessity of simultaneous advancements in sorbent material design and electric-to-thermal conversion efficiency. **Despite these promising outcomes, the present study has limitations in that the system-scale deep learning model was trained on simulated data without validation against real occupancy measurements, and the system-level analysis was**

conducted under simplified boundary conditions. Furthermore, the occupancy scenarios were constrained to 1–4 persons based on a typical residential setting, which may not fully capture the variability of other building types. The same analytical framework is, however, expected to be extendable to other occupancy conditions and building environments by adjusting the relevant input parameters. Future work incorporating building-scale experiments under real-world occupancy conditions, alongside safety validation of the regeneration process in occupied environments, will be essential to fully validate the proposed system toward real-world adoption. Nevertheless, by linking material innovation with system-level implementation, this work provides a meaningful step toward scalable CO₂ control in buildings. ~~By linking material innovation with system-level implementation, this work provides a practical approach toward scalable, energy-efficient CO₂ capture in buildings~~

Reviewer #3 (Remarks to the Author):

This manuscript reports a novel strategy that integrates a Joule-heating-driven CO₂ capture filter into a DAC-controlled ventilation system. Although the proposed Joule-heating regeneration module and adaptive control scheme show potential for improving energy efficiency, quantitative performance comparison with existing CO₂ capture materials and DAC technologies is lacking, and a comprehensive system-level energy and CO₂ emission assessment is not provided. I therefore recommend that the authors to supplement systematic comparative analyses to further clarify and refine the research innovation before resubmission.

1. Innovation in system optimization is not clearly reflected in the title and abstract, and Fig. 1 offers limited insight into the overall system design and performance advantages.

Answer: We sincerely appreciate the reviewer's valuable comment. As pointed out, the concept of system optimization was not reflected in the original title. Accordingly, we have revised the title as "Joule-heating regenerable CO₂ capture filter: From material design to system optimization for indoor applications", placing greater emphasis on the proposal and fabrication of a CO₂ capture filter geometry for ventilation system application, as well as the system operation optimization conducted to evaluate the feasibility of ventilation system integration. In addition, content related to optimization has been incorporated into the abstract to further address the reviewer's comment. Furthermore, since the original Fig. 1 was primarily focused on the CO₂ capture filter geometry, a new Fig. 1 has been added to the manuscript to illustrate the operational concept of the overall ventilation system integrated with the CO₂ capture filter. Thank you.

Before:

Title: Joule-heating regenerable CO₂ capture filter: From material to system application

After:

Title: Joule-heating regenerable CO₂ capture filter: From material design to system optimization for indoor applications

Before:

Abstract

Carbon dioxide (CO₂) plays a key role in indoor air quality and is traditionally managed through ventilation, which often increases energy consumption. To overcome this challenge, we propose a demand-controlled ventilation system integrated with a CO₂ filter (CDCV), which reduces both indoor CO₂ levels and ventilation-related energy use. The modular CO₂ capture filter was manufactured by spray-coating an amine-functionalized solid sorbent onto a carbon fiber substrate, allowing for localized thermal regeneration using Joule heating. This approach enables rapid, safe, and energy-efficient desorption within occupied indoor environments. This research includes material characterization, lab-scale filter tests, and a system-level scenario analysis aiming at translating sorbent technology into real-world

mechanical ventilation systems. System-level analysis showed that proposed system can lower energy loads by about 13.4–25% compared to conventional DCV systems, while maintaining indoor CO₂ at 600 ppm under various outdoor conditions. This work demonstrates a practical pathway to implementation, establishing both the material's effectiveness and the feasibility of integrating such filters into existing building ventilation systems.

After:

Abstract

Carbon dioxide (CO₂) plays a key role in indoor air quality and is traditionally managed through ventilation, which often increases energy consumption. This work proposes a demand-controlled ventilation system integrated with a CO₂ filter (CDCV) to reduce both indoor CO₂ levels and ventilation-related energy use. The modular CO₂ capture filter was manufactured by spray-coating an amine-functionalized solid sorbent onto a carbon fiber substrate, enabling rapid thermal regeneration via Joule heating within 15 min at 100 °C. System-scale operation was optimized using Differential Evolution and a deep neural network to adaptively coordinate filter regeneration and ventilation control under varying indoor conditions. Results show that the proposed system can lower energy loads by about 13.4–25% compared to conventional DCV systems, while maintaining indoor CO₂ at 600 ppm under various outdoor conditions. This work demonstrates a viable implementation pathway, validated through material characterization, lab-scale test, and system-level energy analysis.

Before:

Here, we introduce a scalable CO₂ capture filter designed for direct integration with ventilation systems, enabling localized and energy-efficient regeneration through Joule heating method (Fig. 1).

After (Page 3-4):

Here, we introduce a scalable CO₂ capture filter designed for direct integration with ventilation systems, enabling localized and energy-efficient regeneration through Joule heating method (Fig. 1). The proposed system achieves continuous CO₂ reduction through two distinct operational modes. In the internal circulation mode, an integrated filter removes indoor CO₂, while in the ventilation mode, the filter is regenerated via Joule heating. During regeneration, the desorbed CO₂ is discharged outdoors while fresh ambient air is introduced into the indoors, ensuring a continuous indoor carbon management cycle.

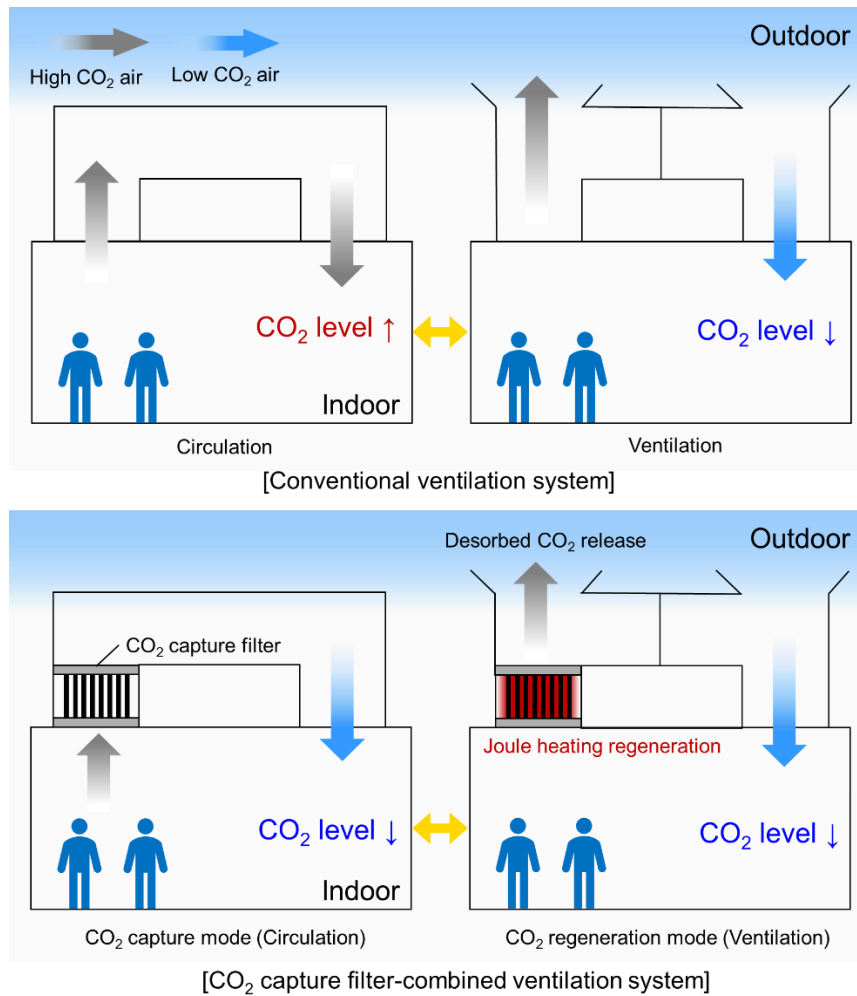


Fig. 1. Conceptual diagram of CO₂ capture filter-combined ventilation system

2. The carbon-fiber-supported polyethyleneimine–silica sorbent does not demonstrate clear innovation at the material level. The authors should assess its performance against state-of-the-art DAC sorbents in terms of CO₂ capture capacity, adsorption/desorption kinetics, regeneration temperature, cycling stability, material cost, and other relevant metrics.

Answer: We thank the reviewer for this comment and the opportunity to clarify the contributions of this work. While the amine-functionalized silica chemistry employed in this study is well-established at the powder level, a significant gap remains between powder-scale sorbent development and device-level implementation suitable for real-world deployment. Most prior studies have focused on maximizing the intrinsic adsorption capacity of powder-form sorbents, whereas the challenges associated with scaling these materials into structured devices, including capacity loss upon structuring, selection of a practical regeneration method compatible with the target application, and integration with existing infrastructure have received considerably less attention. The primary contribution of this work lies in bridging this gap by designing a scalable filter architecture that enables Joule-heating-based in-situ regeneration for indoor CO₂ management, and integrating it with a demand-controlled ventilation system optimized through deep learning-based control. Nevertheless, in response to the reviewer's request, we provide a systematic performance comparison with state-of-the-art DAC sorbents across the specified metrics.

A comprehensive comparison has been added to Supplementary Table 7 and Supplementary Note 8, covering CO₂ capture capacity, desorption kinetics, regeneration temperature, and cyclic stability. The key findings are summarized below.

CO₂ capture capacity

The powder-scale uptake of 1.84 mmol g⁻¹ under 1,000 ppm at 25 °C falls within the range of reported amine-based sorbents. The reduction from 1.84 mmol g⁻¹ (powder) to 1.26 mmol g⁻¹ (coated filter) represents a 31.5% decrease, which is an inherent consequence of transitioning from powder to structured form. As discussed in the manuscript (Fig. 5d), this decline is attributed to dilution of amine content during slurry preparation, structural changes during high-pressure spray deposition, and non-uniform coating distribution. This capacity reduction upon structuring is universally observed across the CO₂ capture literature. For instance, Wu et al.²⁰ reported 0.71 mmol g⁻¹ at 400 ppm for PEI-impregnated silica coated on a ceramic substrate via dip coating; however, their system relies on steam-assisted temperature vacuum swing adsorption (S-TVSA), which requires high-temperature steam supply and is impractical for indoor applications where dedicated steam generation infrastructure is unavailable. Grossmann et al.²¹ reported 0.44 mmol g⁻¹ (pellet) and 0.40 mmol g⁻¹ (monolith) at 400 ppm for triamine-grafted alumina, and Huang et al.²² reported 1.48 mmol g⁻¹ at 2 vol% CO₂ for TEPA-impregnated silica gel pellets with a microcrystalline cellulose binder. In this context, the filter-scale uptake of 1.26 mmol g⁻¹ achieved in the present work at 1,000 ppm is competitive with or exceeds these structured sorbent benchmarks, particularly considering that many of the cited values were measured at substantially higher CO₂ concentrations. Furthermore, the filter-scale uptake exceeds those of other Joule-heating-based fiber systems, such as 0.65 mmol g⁻¹ (Lee et al.¹) and 0.39 mmol g⁻¹ (Lee et al.², Ag-coated fiber basis).

Adsorption/desorption kinetics

The filter demonstrated superior initial adsorption kinetics compared to the powder form within the first 30 minutes (Fig. 5d), attributed to lower film diffusion resistance and thinner

boundary layers in the fiber-aligned structure. For desorption, 95% regeneration was achieved within 15 min at 100 °C and 35 min at 80 °C under atmospheric pressure without vacuum assistance, which is faster than the vacuum-assisted systems reported by Lee et al.¹ (10 min at 110 °C with 0.3 bar vacuum) and Lee et al.² (90-min cycle with partial vacuum). This favorable desorption kinetics is attributed to the use of nonporous silica nanoparticles, which position amine groups on the external particle surface and minimize intra-particle diffusion resistance.

Regeneration temperature

The system operates at 80-100 °C, which is comparable to or lower than other ETSA systems and well below the thermal degradation threshold of the amine functional groups (~150 °C, Fig. 3c).

Cyclic stability

Extended cycling tests over 200 adsorption–desorption cycles at 100 °C confirmed long-term stability, with CO₂ capture capacity showing a slight increase of 2.28% rather than degradation. This compares favorably with 27.6% loss within 40 cycles (Wu et al.³) and 12% loss within 10 humid cycles (Lee et al.²).

Material cost

A techno-economic assessment (TEA) has been added to the revised manuscript (Supplementary Note 7 and Supplementary Table 5). The raw material cost for the consumable filter components (carbon fiber, PEHA, silica nanopowder, and IPA) was quantified based on commercially available unit prices. The break-even analysis (Fig. 9c) demonstrates that the CDCV system recovers its initial capital investment within 48-65 days in summer and 17-18 days in winter under the 600 ppm target condition, confirming that the material and operational costs are offset by the ventilation energy savings within a practically short period.

In summary, while the intrinsic sorbent chemistry is based on established materials, the device-level implementation, encompassing the structured filter design, vacuum-free Joule-heating regeneration, and system-level integration with DCV and deep learning control represents a distinct contribution that addresses the critical gap between powder-scale sorbent research and practical indoor deployment.

Supporting information

After:

Supplementary Table 7. Comparison of electrothermal CO₂ adsorbents with Joule-heating regeneration

Sorbent	Form factor	Heating element	Regeneration Method	Target Application	T _{ads} (K)	T _{des} (K)	t _{des} (min)	CO ₂ Uptake (mmol g ⁻¹)	Cyclic Stability	Ref
PEI/mesoporous silica	Powder coated fiber	Carbon fiber	ETSA VSA	+DAC (400 ppm)	30°C	90-110°C	19min (95%, vacuum-assisted)	0.65 (Filter, 400ppm)	10 cycles	¹
EDA-grafted zeolite	Y Powder coated fiber	Silver nanocomposite	ETSA VSA	+DAC (400 ppm)	25°C	110°C	90min cycle (desorption)	0.39-0.41 (Fiber, 400ppm)	4 cycles (dry, 5% loss) 10 cycles	²

Lee et al.¹⁰ demonstrated sorbent-coated carbon fibers for DAC using PEI-impregnated mesoporous silica, achieving 95% desorption in 10 min at 110 °C under 0.3 bar vacuum. Lee

et al.¹¹ further advanced the electrified fiber concept using silver nanocomposite-coated EDA-grafted Y zeolite fibers, achieving a desorption temperature of 110 °C within 80 s with a partial vacuum-assisted four-step vacuum assisted ETSA cycle (90-min total desorption). Wu et al.¹² proposed a carbon nanofiber (CNF)-based PEI DAC air filter for building ventilation systems, with high uptake capacity (4.0 mmol g⁻¹ under 68% RH at 400 ppm) regenerable via Joule heating and solar thermal energy utilization. However, their system requires off-site regeneration with filter replacement every two days and transportation to centralized processing facilities.

In contrast, the present system achieves rapid desorption under atmospheric pressure, 95% regeneration within 15 min at 100 °C and within 35 min at 80 °C, without vacuum assistance. The favorable desorption kinetics observed in the present system can be attributed to the sorbent and the spray coating process. Lee et al.¹⁰ employed mesoporous silica (SYLOID C-803) in which PEI is confined within mesopore channels, creating substantial intra-particle diffusion resistance during CO₂ release. In the present work, nonporous silica nanoparticles (60-70 nm) were used, positioning the amine functional groups predominantly on the external particle surface and thereby minimizing the CO₂ diffusion pathway during thermal desorption. Additionally, the thin sorbent layer (14.7-46.1 μm) produced by spray coating provides direct thermal contact with the Joule-heated carbon fiber, enabling rapid and uniform heat delivery to the adsorbent. The elimination of vacuum pumps significantly simplifies the system design and removes the associated noise and energy penalty, which is an essential consideration for deployment in occupied indoor spaces.

The filter-scale CO₂ uptake of 1.26 mmol g⁻¹ (1.84 mmol g⁻¹ at the powder scale) under 1,000 ppm at 25 °C is comparable to or exceeds those of other fiber-based ETSA systems on a coated-fiber mass basis, such as 0.65 mmol g⁻¹ (Lee et al.¹⁰) and 0.39 mmol g⁻¹ (Lee et al.¹¹, Ag-coated fiber basis). The system also demonstrated superior cyclic stability, retaining full CO₂ capture capacity with a 2.28% increase over 200 adsorption-desorption cycles, compared to the 27.6% capacity loss within 40 cycles reported for the CNF-based adsorbent by Wu et al.¹². Finally, unlike all cited studies that remain at the material-level demonstration, this work extends to system-level validation by integrating the CO₂ capture filter with a demand-controlled ventilation (DCV) framework and deep learning-based real-time control, achieving up to 28.3% ventilation energy savings compared to conventional DCV systems.

Among other state-of-the-art structured DAC sorbents, Wu et al.¹⁸ reported 0.71 mmol g⁻¹ at 400 ppm using PEI-impregnated silica on a ceramic substrate, though their system requires steam-assisted temperature vacuum swing adsorption (S-TVSA) with high-temperature steam supply, which is impractical for indoor applications.

It is also worth noting that alternative CO₂ capture strategies were considered but deemed unsuitable for the intended indoor application. Liquid amine scrubbing (e.g., aqueous MEA solutions) requires regeneration temperatures of 120-140 °C¹⁹ with reboiler duties of 3.8-4.2 GJ t⁻¹CO₂^{20,21}, and is known to emit volatile degradation products including ammonia, aldehydes, and potentially carcinogenic nitrosamines during thermal cycling²², posing unacceptable health risks in enclosed indoor spaces where stack-based atmospheric dispersion is unavailable. Metal-organic frameworks, while offering high surface areas and tunable pore structures, suffer from significant capacity reduction under humid conditions²³ and involve more complex and costly synthesis processes compared to commercially available amine-functionalized silica²⁴. Zeolite-based physisorbents typically require regeneration temperatures of 150-250 °C²⁵ and exhibit up to 93% capacity loss at 74% relative humidity²⁶, making them incompatible with the moderate-temperature, humidity-

tolerant operation required for indoor environments.

After:

Supplementary Note 7

Techno-economic assessment

The techno-economic assessment was conducted to quantify the economic feasibility of the proposed CDCV system relative to a conventional DCV system. The analysis considered the additional cost associated with filter fabrication, regeneration electricity consumption, and periodic replacement, together with the economic benefit obtained from reducing ventilation-related energy demand. Since the system performance in this study was evaluated on a daily basis, the economic analysis was also formulated using daily energy consumption and daily operating cost as the basic units

The system boundary for energy demand calculation was defined at the ventilation unit level, with the conventional DCV system taken as the reference case and the proposed CDCV system taken as the target case. Only the components and energy terms directly affected by integration of the CO₂ capture filter were included in the economic assessment. Under this definition, the reference DCV system was assumed to incur only the ventilation-related thermal conditioning load associated with the introduction of outdoor air, whereas the CDCV system incurred both the reduced ventilation load and the electrical energy required for Joule-heating regeneration of the filter.

The total cost of the CDCV system was divided into initial capital expenditure (CAPEX) and daily operating expenditure (OPEX). The initial capital expenditure of the CDCV system was defined as a one-time investment required for system installation. This cost includes the housing structure, copper electrodes, electrical wiring, and assembly and installation components necessary to operate the Joule-heating filter module:

$$\text{CAPEX}_{\text{CDCV}} = C_{\text{housing}} + C_{\text{wire}} + C_{\text{copper}} \cdot N_{\text{cell}} + C_{\text{install}} \quad (\text{S24})$$

where N_{cell} is the total number of cells. The installation cost of the filter was assumed to be 20% of the direct equipment cost. Components were assumed to remain intact over the system lifetime and were therefore not subject to periodic replacement.

In contrast, the functional materials responsible for CO₂ capture and regeneration were treated as consumable components and included in OPEX. These materials consist of carbon fiber, amine (PEI), silica, and IPA, which form the active adsorption and coating layer of the filter. Accordingly, the replacement cost was defined based on the periodic interval of these consumable materials.

$$\text{OPEX}_{\text{CDCV,replace}} = (C_{\text{carbon fiber}} + C_{\text{PEI}} + C_{\text{silica}} + C_{\text{IPA}}) \cdot N_{\text{cell}} \quad (\text{S25})$$

Assuming a fixed replacement interval, the replacement cost was converted into an equivalent daily maintenance cost to ensure consistency with the day-based energy analysis. The daily replacement cost was therefore expressed as

$$\text{OPEX}_{\text{CDCV,replace,day}} = \text{OPEX}_{\text{CDCV,replace}} / N_{\text{interval}} \quad (\text{S26})$$

where N_{interval} is the replacement interval expressed in days.

In addition to the replacement cost, the operating expenditure of the CDCV system includes the electricity cost associated with Joule-heating regeneration. The daily regeneration energy consumption obtained from the system simulation was converted into a daily electricity cost using the applicable electricity tariff:

$$\text{OPEX}_{\text{CDCV,regen,day}} = E_{\text{regen,day}} \cdot P_{\text{elec}} \quad (\text{S27})$$

where $E_{\text{regen,day}}$ is the daily regeneration energy consumption and P_{elec} is the unit electricity price. Accordingly, the total daily operating expenditure of the CDCV system was defined as the sum of ventilation energy load, regeneration electricity cost and daily replacement cost:

$$\text{OPEX}_{\text{CDCV,day}} = E_{\text{CDCV,day}} \cdot P_{\text{elec}} + \text{OPEX}_{\text{CDCV,regen,day}} + \text{OPEX}_{\text{CDCV,replace,day}} \quad (\text{S28})$$

For the reference DCV system, the daily operating expenditure consists only of the ventilation-related energy cost, which was calculated from the daily ventilation energy demand:

$$\text{OPEX}_{\text{DCV,day}} = E_{\text{DCV,day}} \cdot P_{\text{elec}} \quad (\text{S29})$$

The economic performance of the CDCV system can be evaluated based on the balance between the reduced ventilation energy cost and the additional costs associated with filter regeneration and material replacement. Thus, the daily net cost saving (CS) achieved by the CDCV system was defined as the difference between the operating expenditures of the reference and proposed systems:

$$\text{CS}_{\text{day}} = \text{OPEX}_{\text{DCV,day}} - \text{OPEX}_{\text{CDCV,day}} \quad (\text{S30})$$

which represents the net economic benefit obtained from reducing ventilation energy demand while accounting for regeneration and replacement costs. Furthermore, the simple payback period was then calculated by comparing the initial investment for proposed system with the daily net cost saving:

$$\text{Payback period} = \frac{\text{CAPEX}_{\text{CDCV}}}{\text{CS}_{\text{day}}} \quad (\text{S31})$$

This metric indicates the time required for the cumulative operating cost savings to recover the additional capital investment associated with the CDCV system.

Supplementary Table 5. Raw materials and unit prices used for fabrication of the CDCV filter module.

Material	Unit	Price (\$)	Supplier
Carbon fiber	5,000 m	147	Fiberman
Polyethylenimine (PEI 600)	1 L	121	Sigma Aldrich
Silica nanopowder (60–70 nm)	1 kg	440	Koreanano

Copper rod ($\Phi 5$ mm)	1 m	1.5	-
Electrical wire	1 m	0.3	-
Isopropyl alcohol (IPA)	4 L	16	Sigma Aldrich
Module housing(20 cm $\times$ 20 cm)	1 ea	6.5	-

3. Joule-heating-based DAC CO₂ regeneration has already been reported (Advanced Materials, 2025, 37(45): e04542; Joule, 2023, 7(6): 1241–1259; Science Advances, 2025, 11(42): eadv6846). The manuscript does not clarify the performance advantages of the proposed filter over these existing approaches, nor does it provide quantitative comparisons of regeneration energy with industrial methods such as temperature or vacuum swing desorption. In addition, thermophysical properties of the filter, including thermal conductivity and heat capacity, should be reported, and temperature distribution during Joule-heating operation should be provided and cross-validated with thermocouple measurements.

Answer: We sincerely thank the reviewer for this thorough and constructive comment, and for bringing the three cited studies to our attention. We have carefully examined each reference and conducted a comprehensive comparison, which has been incorporated into both the revised manuscript and the Supplementary Information.

1. Comparison with cited Joule-heating-based studies.

A new comparison table (Supplementary Table 7) has been added to systematically compare the proposed CO₂ capture filter with the three cited studies and additional electrothermal CO₂ capture literature in terms of sorbent type, form factor, heating element, regeneration method, target CO₂ concentration, operating temperatures, desorption time, uptake capacity, and cyclic stability.

As summarized in Supplementary Table 7, the following key distinctions differentiate the present work from prior Joule-heating-based studies:

(1) Application target: All three cited studies target direct air capture (DAC) at 400 ppm CO₂. To our knowledge, the present work is the first to apply Joule-heating-based regeneration specifically to indoor CO₂ management at 1,000-2,000 ppm.

(2) Rapid vacuum-free desorption: The proposed filter achieves rapid desorption under atmospheric pressure: 95% regeneration within 15 min at 100 °C and within 35 min at 80 °C, without vacuum assistance. In comparison, Lee et al.¹ required vacuum assistance (0.3 bar) to achieve 95% desorption in 10 min at 110 °C, and Lee et al.² employed a combined ETSA process with partial vacuum and a 90-min desorption cycle. The favorable desorption kinetics observed in the present system can be attributed to the sorbent and the spray coating process. Unlike the mesoporous silica (SYLOID C-803) employed by Lee et al.¹, which confines PEI within mesopore channels and introduces significant intra-particle diffusion resistance during CO₂ desorption, the nonporous silica nanopowder (60-70 nm) used in this work positions the amine functional groups predominantly on the external particle surface. This surface-accessible configuration substantially shortens the CO₂ diffusion pathway during thermal desorption, enabling effective regeneration without vacuum-assisted driving force. Furthermore, the thin sorbent layer (14.7-46.1 μ m) formed by spray coating ensures intimate

thermal contact with the Joule-heated carbon fiber, facilitating rapid and uniform heat transfer to the adsorbent. The elimination of vacuum pumps significantly simplifies the system design and removes the associated noise and energy penalty, which is an essential consideration for deployment in occupied indoor spaces.

(3) In-situ regeneration: Wu et al.³ proposed a conceptually related approach of integrating CO₂ capture filters into ventilation systems. However, their system requires off-site regeneration with filter replacement every two days and transportation to centralized processing facilities. Our system enables in-situ regeneration through direct Joule heating of the carbon fiber substrate, allowing continuous autonomous cycling without filter removal.

(4) CO₂ uptake and cyclic stability: The filter-scale CO₂ uptake of 1.26 mmol g⁻¹ (1.84 mmol g⁻¹ at the powder scale) under 1,000 ppm at 25 °C is comparable to or exceeds those of other fiber-based ETSA systems on a coated-fiber mass basis, such as 0.65 mmol g⁻¹ (Lee et al.¹) and 0.39 mmol g⁻¹ (Lee et al.², Ag-coated fiber basis). Furthermore, the filter demonstrated stable cyclic performance over 200 adsorption–desorption cycles at 100 °C with a 2.28% capacity increase rather than degradation, which compares favorably with the 27.6% capacity loss within 40 cycles reported for the CNF-based adsorbent by Wu et al.³.

(5) System-level integration: Unlike all cited studies that remain at the material-level demonstration, this work uniquely extends to system-level validation, integrating the CO₂ capture filter with a demand-controlled ventilation (DCV) framework and deep learning-based real-time control, achieving up to 28.3% ventilation energy savings compared to conventional DCV systems.

A corresponding discussion has been added to Supplementary Note 8

2. Quantitative comparison of regeneration energy with TSA/VSA

As reported in the comprehensive ETSA review by Patil et al.³², conventional TSA systems require 3.23–3.82 MJ kg⁻¹ CO₂, while VPSA systems require 2.37–2.44 MJ kg⁻¹ CO₂. ETSA systems have demonstrated values as low as 1.9 MJ kg⁻¹ CO₂ (Grande et al.³³). In our system, the regeneration energy was quantified using the formulation presented in Supplementary Note 5 (Eq. S18–S20), which accounts for the Joule heating input, sensible heat, and latent heat of desorption. The resulting regeneration energy density at 100 °C was 39.6 Wh m⁻². Furthermore, the total energy comparison at the system level (Supplementary Fig. 16 c-d) demonstrates that the CDCV system achieves up to 28.3% net energy savings compared to the conventional DCV system under winter conditions at 600 ppm, confirming the energy competitiveness of the proposed approach.

In addition, a notable advantage of the ETSA approach over vacuum swing adsorption for indoor applications is the elimination of vacuum pumps, which reduces noise levels, a critical requirement for occupied residential and office environments.

3. Thermophysical properties

The thermophysical properties of the carbon fiber substrate have been added to Supplementary Table 6 in the revised manuscript. The reported values include thermal conductivity (0.105 J/cm s °C), specific heat (0.752 J/g °C), and density (1.78 g/cm³).

4. Temperature distribution and thermocouple cross-validation

Following the reviewer's suggestion, time-resolved thermal imaging of the carbon fiber bundle was conducted using an IR camera under applied voltages of 4–7 V, and the results are

presented in Supplementary Fig. 10 (thermal images) and Supplementary Fig. 11 (temperature-time curves). These measurements confirm that the temperature rises rapidly and reaches a steady-state within approximately 5 seconds, at which point Joule heating and convective heat dissipation reach thermal equilibrium. The surface temperature measured by the IR camera is consistent with the voltage-dependent temperature profiles obtained from thermocouple measurements (Fig. 4b), providing cross-validation of the heating uniformity and thermal response of the carbon fiber filter.

Before:

Supplementary Table 3. Properties of carbon fiber

	Metric	
Tensile Strength	4200	MPa
Tensile Modulus	240	GPa
Strain	1.8	%
Density	1.78	g cm ⁻³
Yield	800	g/1000m

After:

Supplementary Table 6. Properties of carbon fiber

Property	Metric	
Tensile Strength	4200	MPa
Tensile Modulus	240	GPa
Strain	1.8	%
Density	1.78	g/cm ³
Yield	800	g/1000m
Property	Value	
Specific heat	0.752	J g⁻¹ °C⁻¹
Thermal conductivity	0.105	J cm⁻¹ s⁻¹ °C⁻¹

After:

Supplementary Table 7. Comparison of electrothermal CO₂ adsorbents with Joule-heating regeneration

Sorbent	Form factor	Heating element	Regeneration Method	Target Application	T _{ads} (K)	T _{des} (K)	t _{des} (min)	CO ₂ Uptake (mmol g ⁻¹)	Cyclic Stability	Ref
PEI/mesoporous silica	Powder coated fiber	Carbon fiber	ETSA VSA	+DAC (400 ppm)	30°C	90-110°C	19min (95%, vacuum-assisted)	110°C, 0.65 (Filter, 400ppm)	10 cycles	¹
EDA-grafted zeolite	Y Powder coated fiber	Silver nanocomposite	ETSA VSA	+DAC (400 ppm)	25°C	110°C	90min cycle)	(desorption 0.39-0.41 (Fiber, 400ppm)	4 cycles (dry, 5% loss) 10 cycles (humid, 12% loss)	²
PEI/carbon nanofiber	Nonwoven filter	Carbon fiber	ETSA + Solar thermal	Distributed DAC (400 ppm)	25°C	80-105°C	1-2s Joule Heating + ~30min Solar Thermal	1.5 (Filter, 400ppm)	70 cycles (27.6% loss at 40cycles, then stable)	³
Amine-based ion exchange resin/Ag-coated glass flakes	3D-printed monolith	Ag-coated glass flakes	ETSA	DAC (400 ppm)	25°C	70°C	~1 min Joule Heating + ~60 min cycle	1.5 (Monolith, 9vol%, Dry) 0.5 (Monolith, 400ppm, Dry)	10 cycles	⁴
PEI/mesoporous carbon spheres	Spherical particles	Mesoporous carbon spheres	ETSA	Post-combustion (5-15%)	75°C	110°C	30min (ETSA)	3.7 (Powder, 15% CO₂, 75°C, Dry) 4.3 (Powder, 15% CO₂, 75°C, RH 60%)	10 cycles (3% loss)	⁵
SiC-PEI fiber CNT-zeolite fiber	Hollow fiber bundle	SiC or CNT	ETSA VSA	+Post-combustion (15%)	30°C	80-140°C	N/A	0.19 (SiC-PEI, 15% CO₂, Dry) 2.32 (CNT-zeolite, Fiber, 15% CO₂, Dry)	N/A	⁶
Zeolite nanocrystals/carbon foam	Ti-Beta Microcellular carbon foam	Carbon foam	ETSA	Post-combustion (0.15-1bar)	25°C	90-200°C	20min (87%, vacuum-free)	150°C, 4.6 (Powder, 1bar)	30 cycles (30% loss)	⁷
Zeolite NaUSY/activated carbon	Extruded monolith	Activated carbon	ETSA	Post-combustion (<10% CO ₂)	30°C	100-150°C	N/A	2.23 (Monolith, 20kPa)	N/A	⁸
PEI/nonporous silica	Powder coated fiber	Carbon fiber	ETSA	Indoor (1000-2000ppm)	25°C	60-100°C	15min (95%, vacuum-free) 35min (95%, vacuum-free)	100°C, 1.84 (Powder, 1000ppm) 80°C, 1.26 (Filter, 1000ppm)	200 cycles (2.4% mass loss, no capacity loss)	This Work

PEI : Polyethylenimine

EDA : Ethylenediamine

ETSA : Electrothermal Swing Adsorption

VSA : Vacuum Swing Adsorption

Supplementary Note 8. Comparison with existing electrothermal CO₂ capture systems

To contextualize the performance of the proposed CO₂ capture filter, a systematic comparison with recently reported Joule-heating-based electrothermal adsorbents was conducted (Supplementary Table 7). Prior ETSA studies have predominantly targeted either direct air capture (DAC) at 400 ppm or post-combustion flue gas at 5-15 vol% (50,000-150,000 ppm). To our knowledge, no previous study has applied Joule-heating-based regeneration to indoor CO₂ management at concentrations of 1,000-2,000 ppm.

Lee et al.¹⁰ demonstrated sorbent-coated carbon fibers for DAC using PEI-impregnated mesoporous silica, achieving 95% desorption in 10 min at 110 °C under 0.3 bar vacuum. Lee et al.¹¹ further advanced the electrified fiber concept using silver nanocomposite-coated EDA-grafted Y zeolite fibers, achieving a desorption temperature of 110 °C within 80 s with a partial vacuum-assisted four-step vacuum assisted ETSA cycle (90-min total desorption). Wu et al.¹² proposed a carbon nanofiber (CNF)-based PEI DAC air filter for building ventilation systems, with high uptake capacity (4.0 mmol g⁻¹ under 68% RH at 400 ppm) regenerable via Joule heating and solar thermal energy utilization. However, their system requires off-site regeneration with filter replacement every two days and transportation to centralized processing facilities.

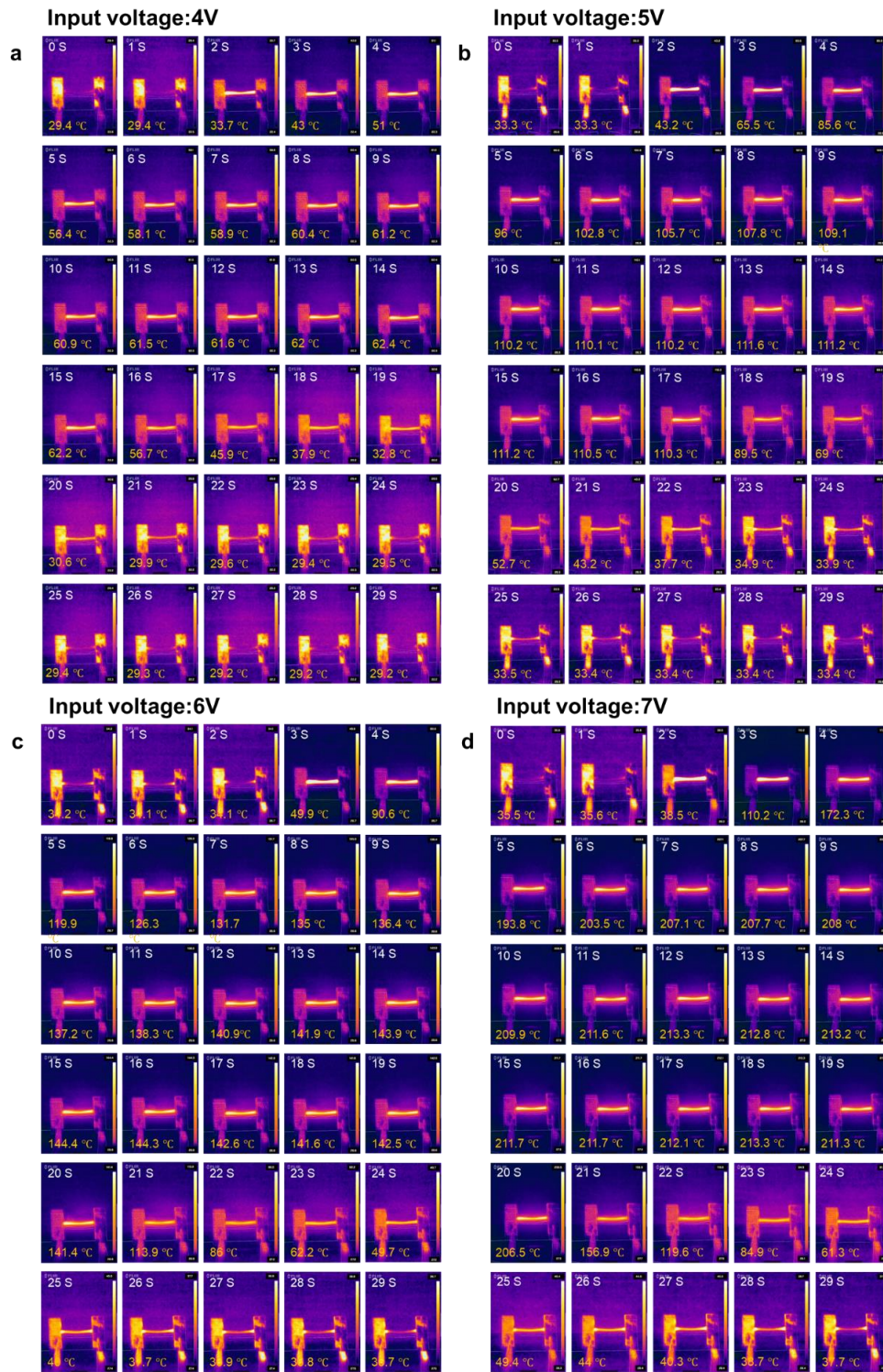
In contrast, the present system achieves rapid desorption under atmospheric pressure, 95% regeneration within 15 min at 100 °C and within 35 min at 80 °C, without vacuum assistance. The favorable desorption kinetics observed in the present system can be attributed to the sorbent and the spray coating process. Lee et al.¹⁰ employed mesoporous silica (SYLOID C-803) in which PEI is confined within mesopore channels, creating substantial intra-particle diffusion resistance during CO₂ release. In the present work, nonporous silica nanoparticles (60-70 nm) were used, positioning the amine functional groups predominantly on the external particle surface and thereby minimizing the CO₂ diffusion pathway during thermal desorption. Additionally, the thin sorbent layer (14.7-46.1 μm) produced by spray coating provides direct thermal contact with the Joule-heated carbon fiber, enabling rapid and uniform heat delivery to the adsorbent. The elimination of vacuum pumps significantly simplifies the system design and removes the associated noise and energy penalty, which is an essential consideration for deployment in occupied indoor spaces.

The filter-scale CO₂ uptake of 1.26 mmol g⁻¹ (1.84 mmol g⁻¹ at the powder scale) under 1,000 ppm at 25 °C is comparable to or exceeds those of other fiber-based ETSA systems on a coated-fiber mass basis, such as 0.65 mmol g⁻¹ (Lee et al.¹⁰) and 0.39 mmol g⁻¹ (Lee et al.¹¹, Ag-coated fiber basis). The system also demonstrated superior cyclic stability, retaining full CO₂ capture capacity with a 2.28% increase over 200 adsorption-desorption cycles, compared to the 27.6% capacity loss within 40 cycles reported for the CNF-based adsorbent by Wu et al.¹². Finally, unlike all cited studies that remain at the material-level demonstration, this work extends to system-level validation by integrating the CO₂ capture filter with a demand-controlled ventilation (DCV) framework and deep learning-based real-time control, achieving up to 28.3% ventilation energy savings compared to conventional DCV systems.

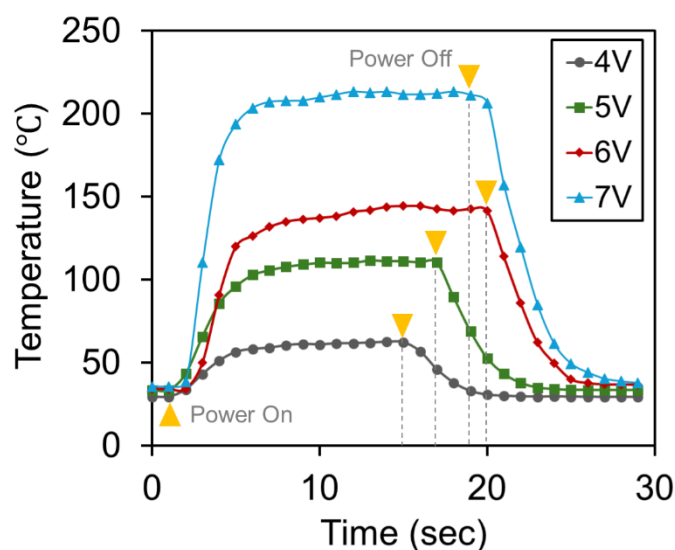
Among other state-of-the-art structured DAC sorbents, Wu et al.¹⁸ reported 0.71 mmol g⁻¹ at 400 ppm using PEI-impregnated silica on a ceramic substrate, though their system requires steam-assisted temperature vacuum swing adsorption (S-TVSA) with high-temperature steam supply, which is impractical for indoor applications.

It is also worth noting that alternative CO₂ capture strategies were considered but deemed unsuitable for the intended indoor application. Liquid amine scrubbing (e.g., aqueous MEA solutions) requires regeneration temperatures of 120-140 °C¹⁹ with reboiler duties of 3.8-4.2

GJ t⁻¹CO₂^{20,21}, and is known to emit volatile degradation products including ammonia, aldehydes, and potentially carcinogenic nitrosamines during thermal cycling²², posing unacceptable health risks in enclosed indoor spaces where stack-based atmospheric dispersion is unavailable. Metal-organic frameworks, while offering high surface areas and tunable pore structures, suffer from significant capacity reduction under humid conditions²³ and involve more complex and costly synthesis processes compared to commercially available amine-functionalized silica²⁴. Zeolite-based physisorbents typically require regeneration temperatures of 150-250 °C²⁵ and exhibit up to 93% capacity loss at 74% relative humidity²⁶, making them incompatible with the moderate-temperature, humidity-tolerant operation required for indoor environments.



Supplementary Fig. 10. Time-sequential thermal images of a carbon fiber bundle under applied voltages of (a) 4, (b) 5, (c) 6, and (d) 7 V.



Supplementary Fig. 11. Temperature–time curves of a carbon fiber bundle under applied voltages of 4, 5, 6, and 7 V.

After (Page 26):

A systematic comparison with recently reported Joule-heating-based CO₂ capture systems is provided in Supplementary Table 7 and Supplementary Note 8. Lee et al.¹ achieved 95% desorption in 10 min at 110 °C under 0.3 bar vacuum using PEI-impregnated mesoporous silica coated on carbon fibers for DAC. Lee et al.² developed silver nanocomposite-coated zeolite fibers with a partial vacuum-assisted e-TVSA cycle for DAC. Wu et al.³ proposed a carbon nanofiber-based DAC air filter for building ventilation, though requiring off-site regeneration with filter replacement every two days. All three studies target DAC at 400 ppm, whereas the present work applies Joule-heating-based regeneration to indoor CO₂ at 1,000–2,000 ppm. The proposed filter achieves vacuum-free desorption (95% within 15 min at 100 °C), enabled by nonporous silica nanoparticles that minimize intra-particle diffusion resistance and a thin sorbent layer (14.7–46.1 μm) ensuring direct thermal contact with the carbon fiber. The filter-scale uptake of 1.26 mmol g⁻¹ exceeds those of comparable fiber-based systems (0.65 mmol g⁻¹; 0.39 mmol g⁻¹), with stable cycling performance over 200 cycles (Supplementary Fig. 3).

4. When testing filter performance in the custom-built setup, key structural parameters (such as fiber winding number or packing density) are not specified. These parameters directly affect pressure drop, which in turn influences fan power consumption in ventilation systems and overall system energy consumption. Such parameters should be measured and reported in the experimental characterization.

Answer: Thank you for your valuable comment. As pointed out by the reviewer, the key structural parameters (such as fiber winding number and packing density) had not been reported in the manuscript or Supplementary information, despite being used in our calculations. We have added a Supplementary Table 2 summarizing the key structural parameters of the filter used in the lab-scale experiments. Additionally, since reliable

differential pressure measurement was not feasible within the custom-built closed-loop setup at the operating flow velocity (~ 3 m/s), CFD simulations were performed as an alternative. The CFD results indicated that, assuming a $10\text{ cm} \times 10\text{ cm}$ flow channel with 9 cells installed, the additional fan power demand due to the filter pressure drop was estimated to be approximately 3.4%, which was considered negligible. This finding is now stated in the main text as the basis for excluding the additional fan power from the energy consumption calculations. Thank you.

Before:

Laboratory scale CO₂ adsorption & desorption experiments

Breakthrough adsorption test is widely employed to evaluate the performance of CO₂ adsorbents at the lab-scale and serves as a standard performance metric. However, its applicability to actual ventilation systems is limited due to the high pressure drop, since these systems already incorporate pressure-inducing components such as **High Efficiency Particulate Air (HEPA)** filters and heat exchangers. In this study, the performance of the carbon fiber CO₂ capture filter was assessed using a batch-type acrylic chamber setup (Fig. 4a), which facilitates internal air circulation, continuous monitoring of CO₂ concentration, and simulates filter placement in realistic ventilation environments. Detailed equipment specifications are provided in Supplementary Table 1.

After (Page 12)

Laboratory scale CO₂ adsorption & desorption experiments

Breakthrough adsorption test is widely employed to evaluate the performance of CO₂ adsorbents at the lab-scale and serves as a standard performance metric. However, its applicability to actual ventilation systems is limited due to the high pressure drop, since these systems already incorporate pressure-inducing components such as **High Efficiency Particulate Air (HEPA)** filters and heat exchangers. In this study, the performance of the carbon fiber CO₂ capture filter was assessed using a batch-type acrylic chamber setup (Fig. 5a), which facilitates internal air circulation, continuous monitoring of CO₂ concentration, and simulates filter placement in realistic ventilation environments. Detailed equipment specifications and **the structural parameters of the CO₂ capture filter** are provided in Supplementary Table 1 and Supplementary Table 2. Since direct differential pressure measurement across the filter was not feasible in the lab-scale apparatus, CFD simulations were conducted to characterize the pressure drop. The detailed methodology and boundary conditions are provided in Supplementary Note 1, and the corresponding pressure contour results are shown in Supplementary Fig. 12. The simulated differential pressure ranged from 0.393 Pa (3 cells, 1 m s^{-1}) to 14.144 Pa (9 cells, 3 m s^{-1}). These values represent less than 3.4% variation in fan power demand, which was considered negligible and therefore excluded from the energy calculations.

Supplementary information

Supplementary Table 2. Structural parameters of the CO₂ capture filter and experimental setup.

Parameter	Value
Number of cells	8
Fiber length per cell (cm)	53
Weight of the carbon fiber per length (g/cm)	4.13×10^{-3}
Weight of the coating per length (g/cm)	4.35×10^{-3}
Weight percent of the amine group (%)	50
Weight of the total coated amine group (g)	0.923
Volume of the experimental setup (L)	265
Scale of the acrylic chamber (cm × cm × cm)	$50 \times 50 \times 50$
Scale of the acrylic duct (cm × cm)	10×10
Diameter of the flexible ducts (cm)	13

Supplementary Note 1

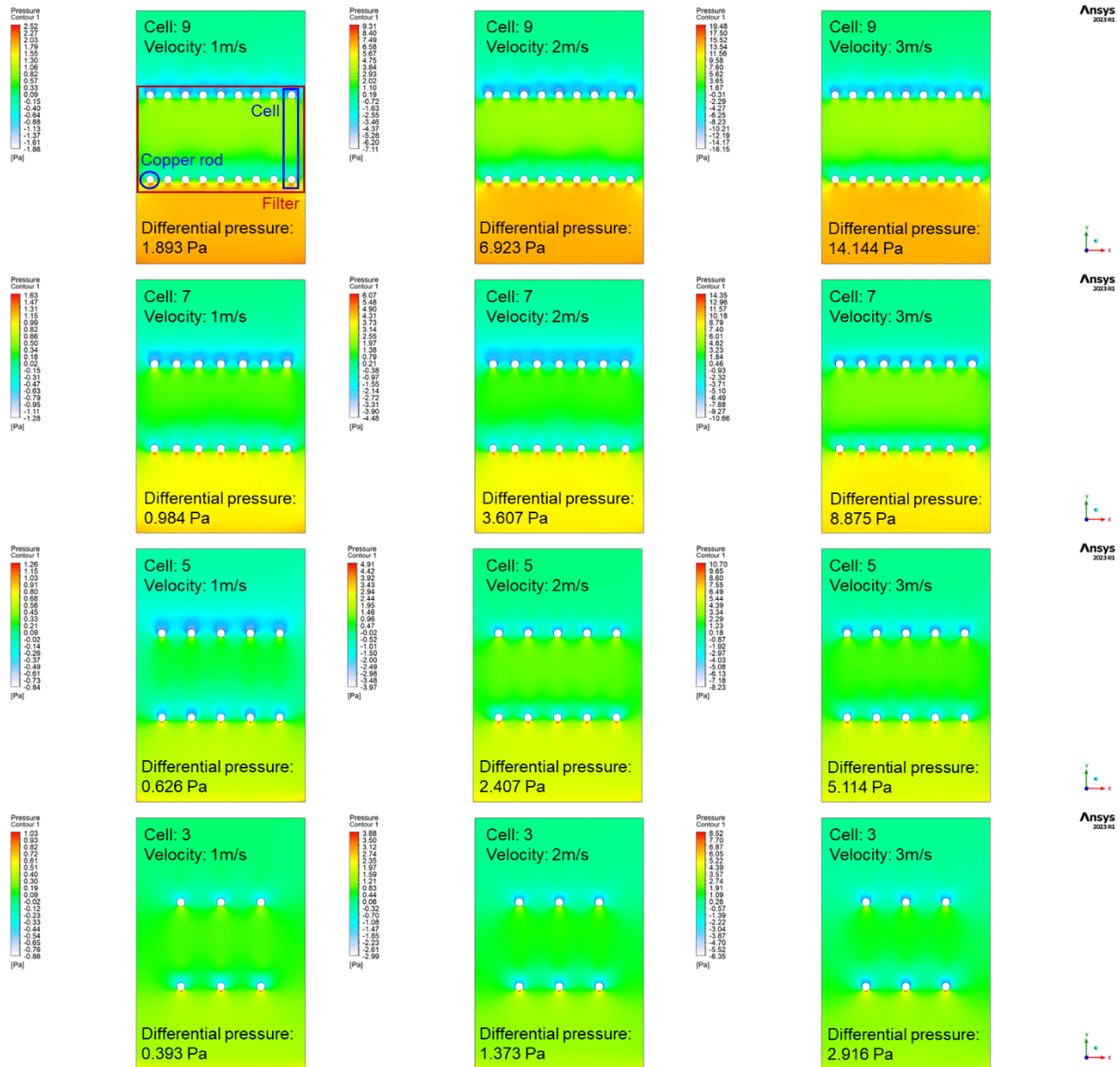
Direct differential pressure measurement across the CO₂ capture filter was not feasible in the lab-scale apparatus. To address this, steady-state CFD simulations were performed using ANSYS Fluent to characterize the pressure drop under representative operating conditions. The computational domain consisted of a rectangular duct with a cross-sectional area of 100 mm × 100 mm. Copper rods with a diameter of 5 mm were placed at the inlet and outlet faces of the filter section to replicate the cell geometry, with cell numbers of 3, 5, 7, and 9. The winding geometry of the carbon fiber was excluded from the domain to simplify the model while preserving the essential flow-blocking characteristics of the filter structure. Inlet velocities of 1, 2, and 3 m/s were applied as boundary conditions, and the differential pressure was defined as the area-averaged static pressure difference between the filter inlet and outlet planes.

The governing equations solved in the simulations are the continuity and momentum equations as follows:

$$\frac{\partial}{\partial t}(\rho) + \nabla \cdot (\rho \vec{u}) = 0 \quad (\text{S1})$$

$$\frac{\partial}{\partial t}(\rho \vec{u}) + \nabla \cdot (\rho \vec{u} \vec{u}) = -\nabla P + \nabla \cdot \left(\mu (\nabla \vec{u} + \nabla \vec{u}^T) \right) + \rho \vec{g} \quad (\text{S2})$$

Turbulence was modeled using the realizable k-ε model with enhanced wall functions. Pressure-velocity coupling was handled via the SIMPLE algorithm, and spatial discretization employed second-order upwind schemes for both momentum and pressure.



Supplementary Fig. 12. CFD-simulated pressure contours and differential pressure across the CO₂ capture filter under varying cell numbers and inlet air velocities.

5. Real ventilation air is a multicomponent gas mixture, and polyethyleneimine-based materials are sensible to water molecules. Capture and regeneration performance under varying temperature, humidity, and mixed-gas conditions should therefore be evaluated.

Answer: We thank the reviewer for this important comment. We agree that evaluating performance under realistic multicomponent gas and varying humidity conditions is essential for validating the applicability of amine-based sorbents in real ventilation environments. We address each aspect below.

Mixed-gas conditions

We would like to clarify that the lab-scale experiments presented in this study (Fig. 5) were not conducted using synthetic gas mixtures but rather using real indoor air with controlled CO₂ injection into the closed-loop chamber. The gas composition within the experimental setup therefore closely reflects that of actual indoor air, including N₂, O₂, Ar, and trace components at their natural atmospheric proportions, with CO₂ elevated to the target concentration range of 1,000–2,000 ppm via a mass flow controller. As such, the adsorption and desorption performance reported in this work inherently accounts for the multicomponent nature of real ventilation air, including any competitive adsorption effects from coexisting gas species.

Humidity effects

As the reviewer correctly notes, the interaction between water molecules and amine-functionalized sorbents is a critical factor in determining CO₂ capture performance. To systematically evaluate this, co-adsorption measurements of CO₂ and H₂O were conducted using a DVS-Carbon system under precisely controlled humidity conditions (0, 20, 40, and 60% RH) at 1,000 ppm CO₂ and 25 °C (Fig. 3d, Supplementary Fig. 2). In each measurement, the sorbent was first pre-saturated with water vapor at the target RH under N₂ carrier gas until mass equilibrium was achieved, after which 1,000 ppm CO₂ was introduced to evaluate the subsequent CO₂ uptake. The results revealed a non-monotonic dependence of CO₂ uptake on RH, a modest enhancement was observed at 20% RH relative to the dry condition, attributed to the promotion of bicarbonate formation pathways that increase effective amine utilization efficiency. At higher humidity levels (40% and 60% RH), however, competitive adsorption between H₂O and CO₂ led to a progressive decline in CO₂ uptake. These findings confirm that the sorbent maintains adequate CO₂ capture performance within the typical indoor humidity range (~40% RH), consistent with the lab-scale cycling data (Fig. 5f) obtained under realistic indoor conditions (47–56% RH).

Temperature effects

The influence of temperature on desorption performance was characterized at three regeneration temperatures (60, 80, and 100 °C), as presented in Fig. 5c. Extended 200-cycle tests at each temperature (Supplementary Fig. 3) further confirmed stable performance across the evaluated temperature range, with the operating conditions remaining well below the amine thermal degradation threshold (~150 °C, Fig. 3c).

The corresponding analysis and data have been incorporated into the revised manuscript and Supplementary Information.

After (Page 7):

Figure 3d presents the co-adsorption capacities of CO₂ and H₂O as a function of target relative humidity (RH) for the optimally loaded sorbent (50wt%). Given that the CO₂ adsorption capacity of amine-impregnated sorbents may vary substantially in the presence of water vapor, it was necessary to characterize co-adsorption behavior under controlled humidity conditions. In each measurement, the adsorbent was first pre-saturated with water vapor at a fixed target RH (0%, 20%, 40%, or 60%) under a N₂ carrier gas until mass equilibrium was achieved, after which 1,000 ppm CO₂ was introduced to evaluate the subsequent CO₂ uptake under steady-state humid conditions. H₂O adsorption capacity increased monotonically with target RH, reaching approximately 4.87, 10.46, and 16.61 mmol g⁻¹ at 20%, 40%, and 60% RH, respectively. CO₂ adsorption capacity, by contrast, exhibited a non-monotonic dependence on RH: a modest enhancement was observed at 20% RH relative to the dry condition, followed by a progressive decline at 40% RH and 60% RH conditions. The initial enhancement at low humidity is attributed to a shift in the CO₂ reaction pathway, in which the introduction of moderate water vapor promotes the partial conversion from ammonium carbamate to bicarbonate and carbonate species, increasing the effective amine utilization efficiency and thereby enhancing CO₂ uptake³⁴. At higher humidity levels, however, the accumulation of water within the pore network progressively impedes CO₂ diffusion and occupies adsorption sites in competition with CO₂ molecules, leading to the observed decline in uptake¹⁸. These results suggest that under indoor conditions exceeding approximately 40% RH, competitive adsorption between H₂O and CO₂ may substantially reduce the CO₂ capture performance of the amine-impregnated sorbent. Each co-adsorption measurement was conducted over three consecutive cycles, and the full adsorption curves for all RH conditions are provided in Supplementary Fig. 2.

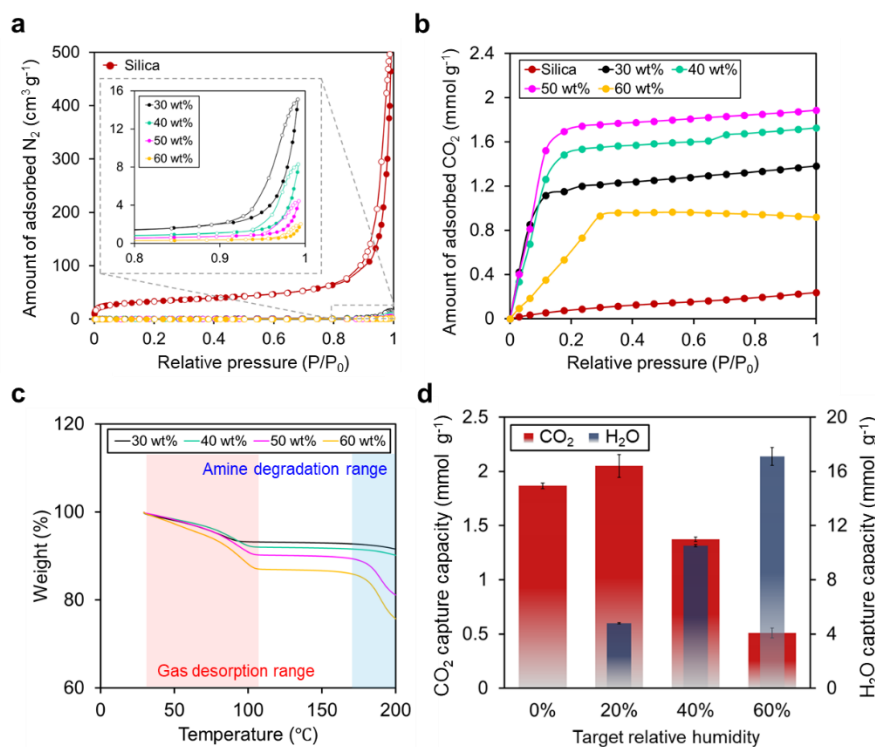
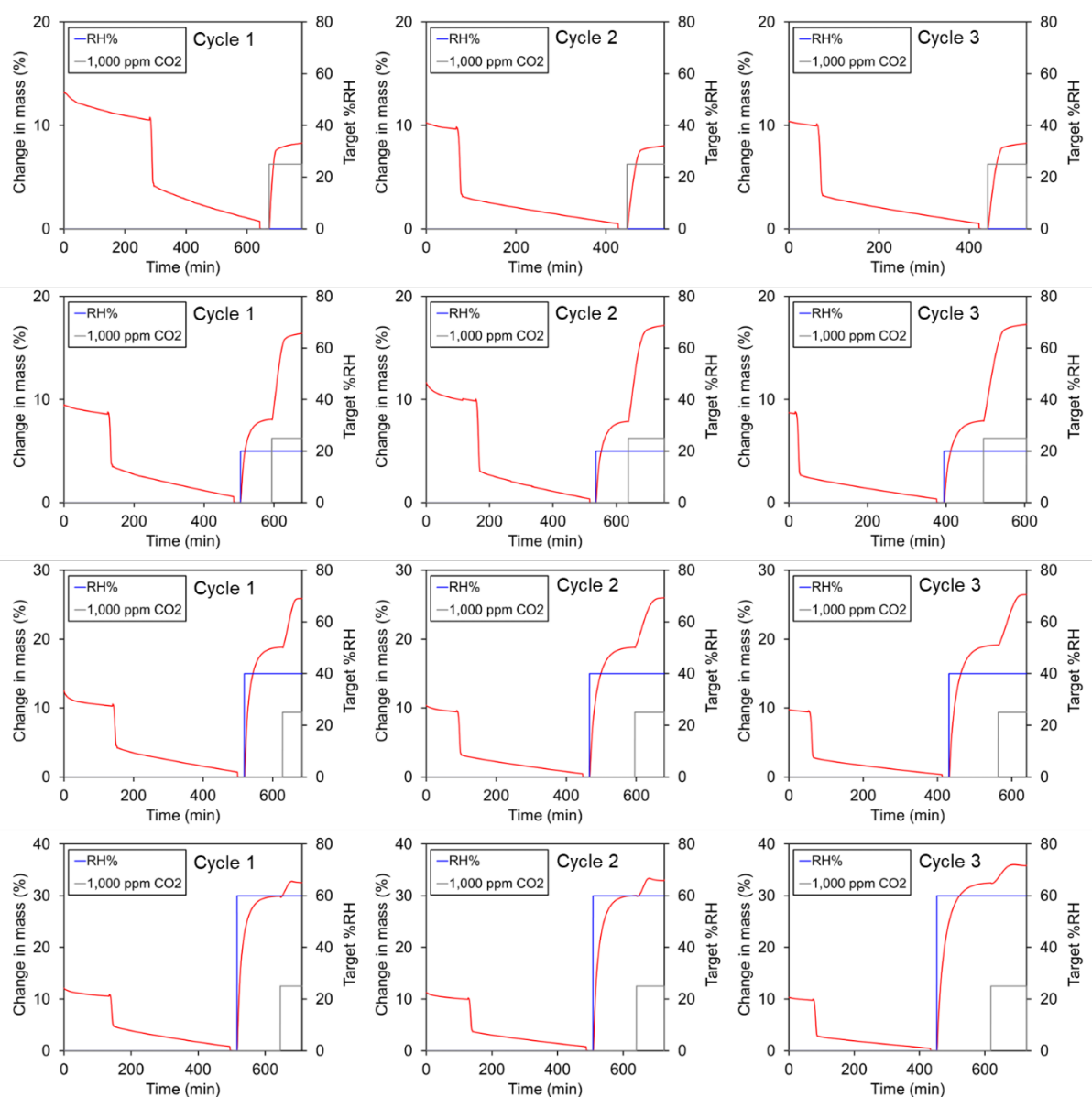
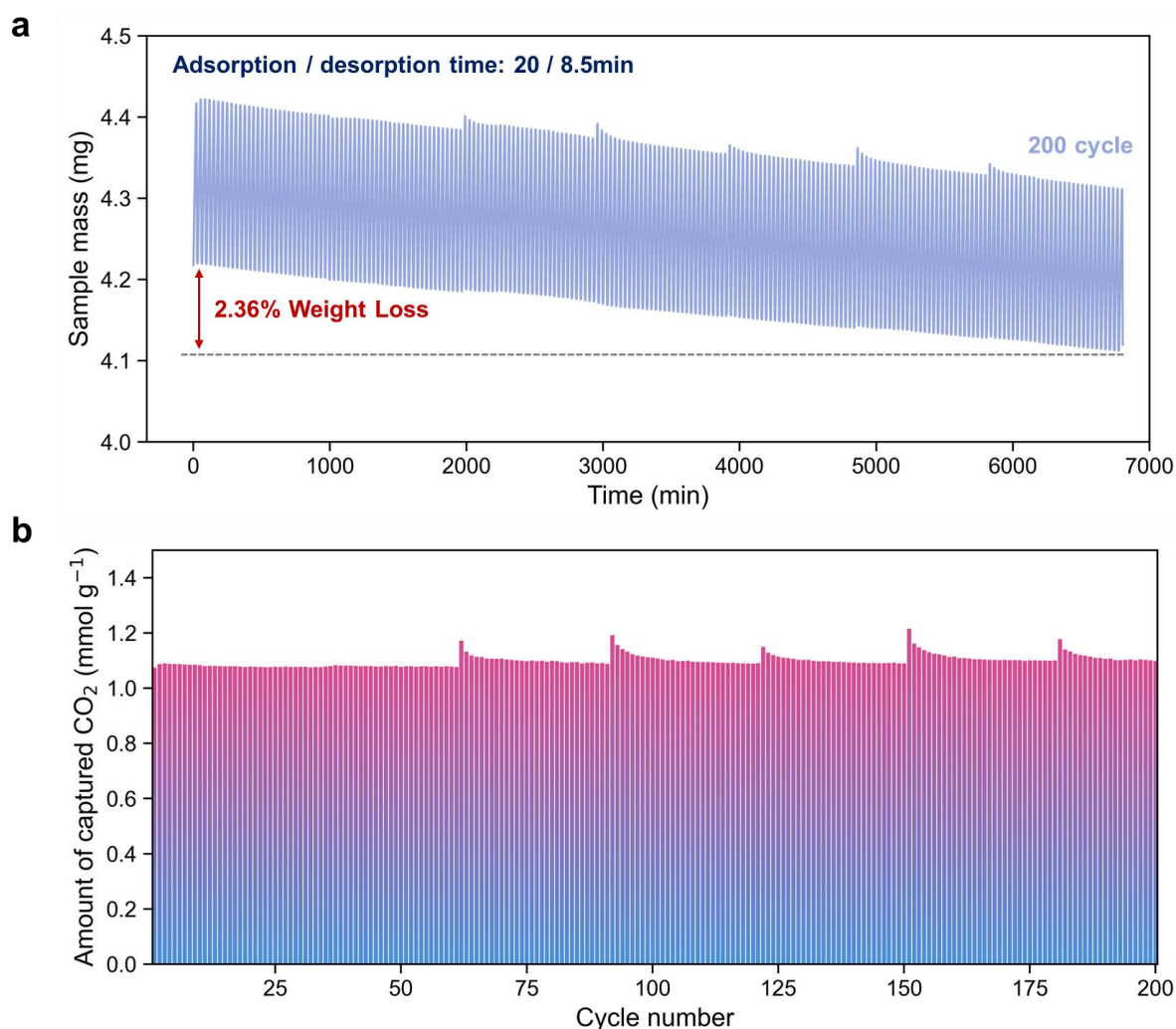


Fig. 3. Characterization data of CO₂ adsorbent (Silica nanopowder). (a) N₂ adsorption curve (b) CO₂ adsorption curve depending on the partial pressure. (c) Thermogravimetric analysis result of the samples. (d) CO₂ and H₂O co-adsorption analysis results.



Supplementary Fig. 2. Full dynamic vapor-carbon sorption mass-change profiles for co-adsorption of H₂O and CO₂ (1,000 ppm) under target relative humidity conditions of 0%, 20%, 40%, and 60% RH.



Supplementary Fig. 3. Long-term cyclic stability of the sorbent-coated carbon fiber filter over 200 adsorption-desorption cycles at regeneration temperature of 100 °C. (a) Thermogravimetric (TG) curve showing the sample mass variation across 200 cycles (b) Amount of captured CO₂ per cycle

After (Page 32-33):

Long-term cyclic stability test

To evaluate the long-term durability of the sorbent under repeated thermal cycling, 200 consecutive partial adsorption–desorption cycles were performed using a simultaneous thermogravimetric analyzer (HITACHI, STA 200). Each cycle consisted of a 20 min adsorption phase at 25 °C under a 1,000 ppm CO₂/N₂ gas flow, followed by desorption via heating to 100 °C at a ramp rate of 10 °C min^{−1} with a 1 min isothermal hold. Because the instrument is limited to 100 programmable temperature steps (approximately 30 cycles per run), the 200-cycle test was completed by performing seven sequential runs under identical conditions.

6. It is recommended to justify why indoor–outdoor air enthalpy differences are adopted for quantifying the energy load. Also, due to the electricity-driven regeneration in the CDCV system, a comparison of the operational CO₂ emissions between CDCV and conventional DCV could help highlight the practical implications.

Answer: We thank the reviewer for the insightful comments. Regarding the use of indoor–outdoor air enthalpy difference for quantifying the energy load, the enthalpy difference between indoor and outdoor air represents the total thermal energy, encompassing both sensible and latent heat that the HVAC system must compensate for when introducing outdoor ventilation air. This metric is widely adopted in building energy analysis as it comprehensively captures the actual energy burden imposed on the conditioning system under varying climatic conditions, making it a physically meaningful and practical basis for energy load quantification.

Secondly, regarding the operational CO₂ emissions comparison between CDCV and DCV, the CDCV system incorporates an additional CO₂ filter that requires electricity-driven regeneration, resulting in additional power consumption compared to conventional system. Rather than conducting a direct operational CO₂ emissions comparison, we performed a comprehensive economic feasibility evaluation as an alternative approach to highlight the practical implications of the two systems. In our additional analysis, all forms of energy consumption in the DCV and CDCV systems were converted into a unified kWh unit and subsequently translated into electricity costs, enabling a direct economic comparison between the two systems. Furthermore, the practical effectiveness of the CDCV system was assessed by incorporating installation and filter replacement costs into the evaluation, providing a more holistic view of its applicability. Since the operational energy consumption of both systems is ultimately expressed in terms of electricity usage and cost, we believe this approach inherently reflects the practical implications of the additional power demand in the CDCV system, including its associated operational carbon footprint. We hope this analysis adequately addresses the reviewer's concern.

Before:

The feasibility of the CDCV system compared to the conventional DCV system was assessed by calculating daily energy loads using average outdoor enthalpy data for summer and winter, along with system-specific operating patterns. The ventilation-induced thermal energy load for each system was estimated based on the average enthalpy difference between outdoor and indoor air, combined with the average ventilation rate and air density. Specifically, the total energy demand was calculated using the following expressions:

After (Page 24):

The feasibility of the CDCV system compared to the conventional DCV system was assessed by calculating daily energy loads using average outdoor enthalpy data for summer and winter, along with system-specific operating patterns. The ventilation-induced thermal energy load for each system was estimated based on the average enthalpy difference between outdoor and indoor air, combined with the average ventilation rate and air density. **The enthalpy difference was adopted as the energy metric, as it covers both sensible and latent heat components that the HVAC system must compensate for when introducing outdoor ventilation air. This makes it a comprehensive and physically meaningful basis for quantifying the actual thermal burden under varying climatic conditions.** Specifically, the total energy demand was calculated using

the following expressions:

After (Page 25):

A techno-economic assessment (TEA) was conducted to evaluate the practical feasibility of the CDCV system by comparing the total daily cost against that of the conventional DCV system across summer and winter conditions and three filter replacement intervals (7, 15, and 30 days) (Fig. 9c). The total cost of the CDCV system was decomposed into four components: capital expenditure (CAPEX) for system installation, ventilation energy cost, Joule-heating regeneration electricity cost, and periodic consumable replacement cost, whereas the DCV system incurred only ventilation-related energy costs (detailed methodology and material costs are provided in Supplementary Note 7 and Supplementary Table 5). As shown in Fig. 9, despite the additional CAPEX and operational costs associated with CO₂ capture and regeneration, the CDCV system achieved a lower cumulative total cost than the DCV system beyond a break-even point in all evaluated scenarios. In summer conditions, the break-even point ranged from 65 days (7-day replacement interval) to 48 days (30-day replacement interval). In winter, the break-even point was markedly shorter, falling within only 17–18 days across all replacement intervals. This pronounced seasonal difference arises because the ventilation thermal load is substantially larger in winter due to the greater temperature differential between indoor and outdoor air, which amplifies the magnitude of ventilation energy savings achievable by the CDCV system and thereby accelerates cost recovery. These results demonstrate that the CDCV system can recover its initial investment within a practically short operational period and deliver sustained cost benefits over time, with the economic advantage being particularly pronounced under cold-climate conditions.

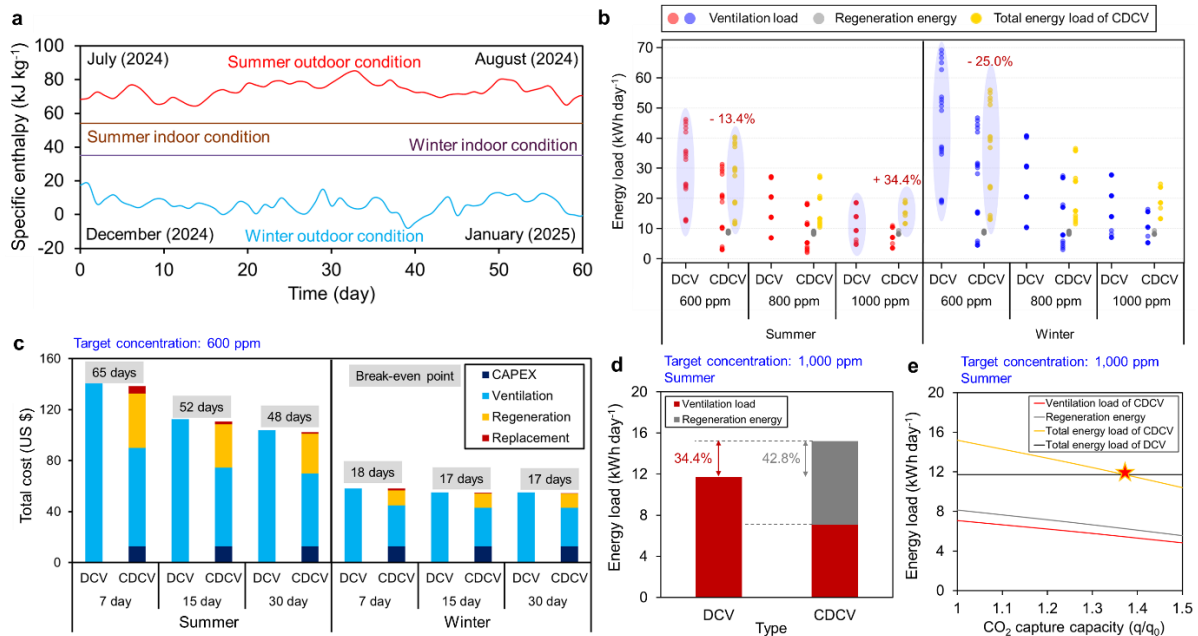


Fig. 9. Feasibility study comparing DCV and CDCV systems. (a) Seasonal variation of indoor/outdoor specific enthalpy under typical summer and winter conditions. **(b)** Comparison of total daily energy demand for DCV and CDCV systems. **(c)** Break-even point analysis based on filter replacement cycle. **(d)** Required reduction in regeneration energy to

achieve energy parity between CDCV and DCV systems. (e) Effect of increasing CO₂ capture capacity on the total energy load of CDCV system.

7. The conclusion that desorption energy consumption is minimized at 100 °C is not supported by sufficient quantitative analysis.

Answer: We sincerely thank the reviewer for this valuable comment. The energy consumed for desorption can be estimated from the temperature versus power density result shown in Fig. 4(f) of the electro-thermal characteristics section, together with the desorption kinetics of the filter. In response to the reviewer's comment, the filter desorption behavior was fitted using the Avrami model, and the time required to reach 95% desorption of the total fraction was determined. This time was then multiplied by the predicted power density equation as a function of target temperature, $J(T)$, to obtain the energy density (Wh/m²). The resulting values were 39.6, 60.7, and 566.8 as the regeneration temperature decreased, and the value at 60°C was approximately 14.3 times higher than that at 100°C. This indicates that even if the input energy required to reach the target temperature is lower, a different trend may appear when desorption kinetics are considered together. The related explanation has been added to the manuscript to further support the choice of 100°C as the target regeneration temperature. Thank you.

Before:

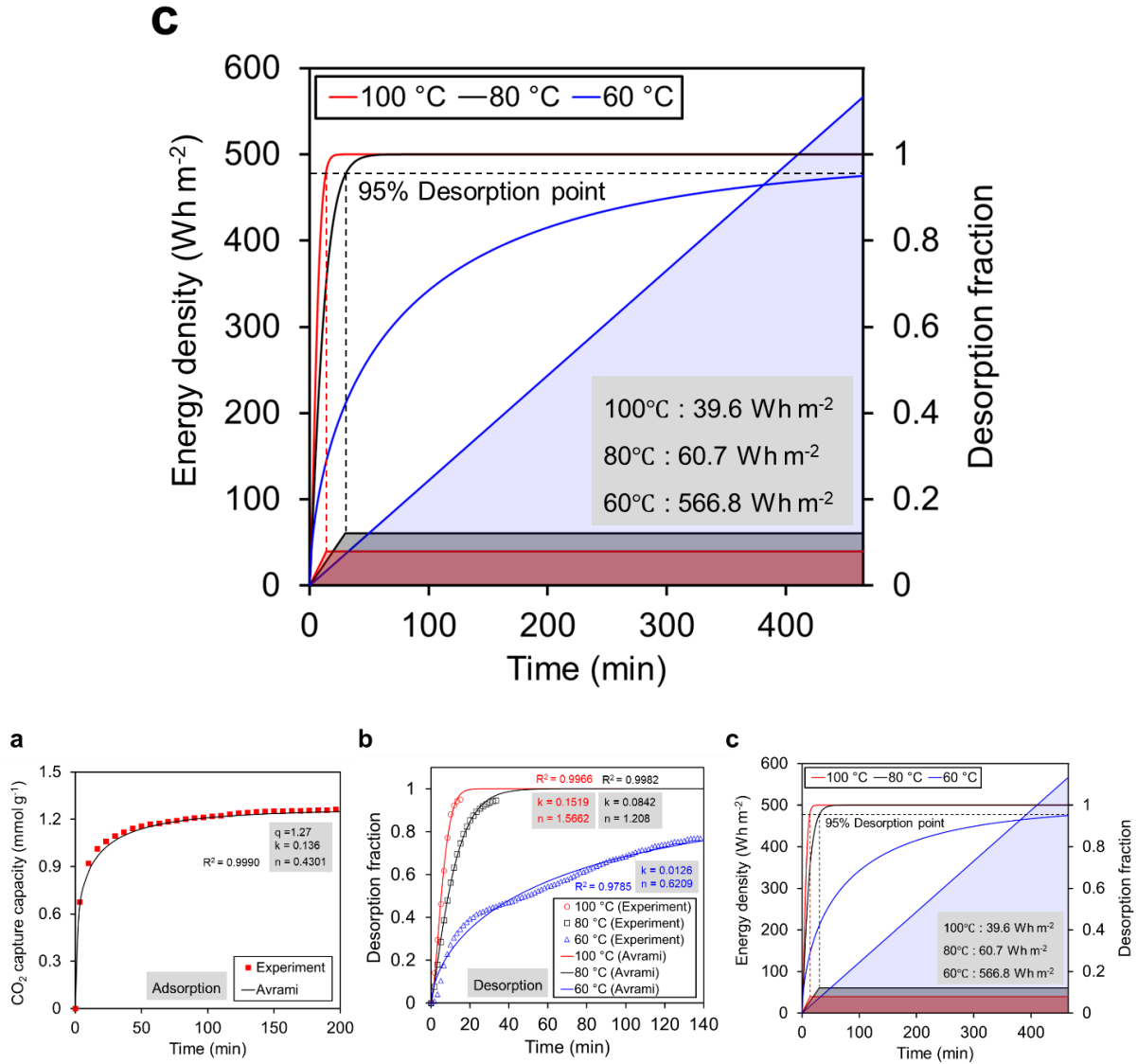
Desorption performance under Joule heating was evaluated by achieving target surface temperatures of 60 °C, 80 °C, and 100 °C through voltage control (Fig. 4c). Although minor temperature fluctuations due to resistance variations ($\pm 5\%$) were observed, stable heating was maintained throughout. The time required to achieve 95% desorption was employed as a consistent performance metric. At 100 °C, 95% regeneration was reached within 15 min, while at 80 °C it required approximately 35 min. Desorption at 60 °C remained incomplete after 120 min, indicating insufficient thermal activation. Despite higher instantaneous power at elevated temperatures, the total energy consumption was lower at 100 °C owing to the significantly reduced operation time. These results highlight the importance of high-temperature Joule heating for efficient and energy-optimized sorbent regeneration.

After (Page 12-13):

Desorption performance under Joule heating was evaluated by achieving target surface temperatures of 60 °C, 80 °C, and 100 °C through voltage control (Fig. 5c). Although minor temperature fluctuations due to resistance variations ($\pm 5\%$) were observed, stable heating was maintained throughout. The time required to achieve 95% desorption was employed as a consistent performance metric. At 100 °C, 95% regeneration was reached within 15 min, while at 80 °C it required approximately 35 min. Desorption at 60 °C remained incomplete after 120 min, indicating insufficient thermal activation. Despite higher instantaneous power at elevated temperatures, the total energy consumption was lower at 100 °C owing to the significantly reduced operation time. To quantitatively support the selection of 100 °C as the target regeneration temperature, the energy density required to reach 95% desorption was estimated by combining the Avrami model-fitted desorption kinetics (Supplementary Fig. 13b) with the empirically derived power density equation $J(T)$ (Fig. 4e). The resulting energy densities were 39.6, 60.7, and 566.8 Wh/m² at 100 °C, 80 °C, and 60 °C, respectively, indicating that operation at 60 °C requires approximately 14.3 times more energy than at 100 °C (Supplementary Fig. 13c). These results confirm that although

higher temperatures demand greater power input, the substantially shorter time required to achieve 95% desorption results in lower total energy consumption, validating 100 °C as the energetically optimal regeneration temperature in this study.

Supplementary information



Supplementary Fig. 13. Avrami model fitting of lab-scale adsorption/desorption kinetics and energy density analysis for Joule heating-based regeneration. (a) Avrami model fitting of CO₂ adsorption kinetics of the sorbent-coated carbon fiber filter. **(b)** Avrami model fitting of CO₂ desorption kinetics at 60, 80, and 100 °C. **(c)** Cumulative energy density required to reach 95% desorption at each target temperature.

8. The Avrami kinetic model is used to describe adsorption/desorption behavior, but experimental data and fitting curves are not provided, making it impossible to assess the validity of the model.

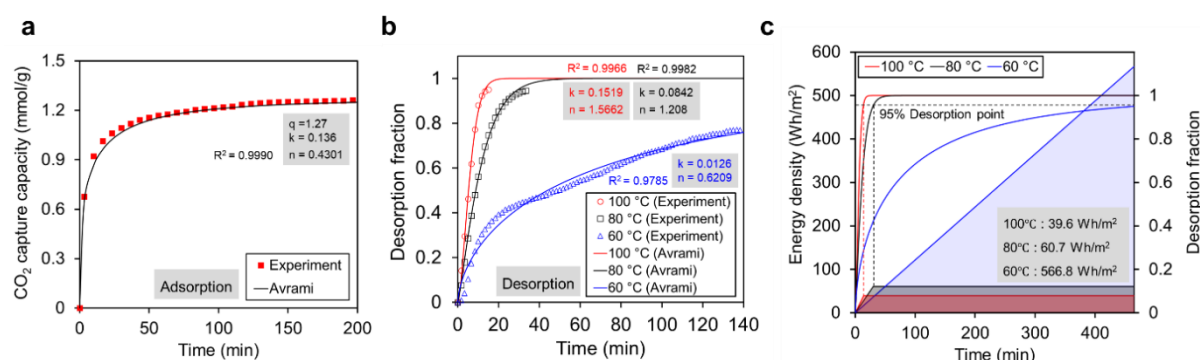
Answer: The reviewer raised an important point. The simulation was performed using the Avrami n and k values for both adsorption and desorption, but the corresponding fitting results were omitted during preparation of the manuscript and the Supplementary information. As suggested by the reviewer, the Avrami fitting results for both the adsorption and desorption profiles have now been added to the Supplementary Information, and the related description has also been incorporated into the manuscript. Thank you.

Before:

Further details on system equations, adsorption and desorption rates, and parameter definitions for R_{occ} and R_{target} , are provided in Supplementary Note 2 and Supplementary Fig. 7.

After (Page 17-18):

Further details on system equations, adsorption and desorption rates, and parameter definitions for R_{occ} and R_{target} , are provided in Supplementary Note 3, **Supplementary Fig 15**.



Supplementary Fig. 13. Avrami model fitting of lab-scale adsorption/desorption kinetics and energy density analysis for Joule heating-based regeneration. (a) Avrami model fitting of CO₂ adsorption kinetics of the sorbent-coated carbon fiber filter. (b) Avrami model fitting of CO₂ desorption kinetics at 60, 80, and 100 °C. (c) Cumulative energy density required to reach 95% desorption at each target temperature.

9. Long-term operation may lead to oxidative aging of the filter material, degrading adsorption capacity and electrothermal performance. The reported 10–20 cycles are insufficient to support claims of long-term applicability, and extended cycling tests are required.

Answer: We thank the reviewer for this important comment. We fully agree that oxidative aging is a relevant concern for amine-based sorbents and that extended cycling tests are essential to support claims of long-term applicability. In response, we have conducted 200-cycle tests, reviewed the oxidation literature, and incorporated a discussion of mitigation strategies into the revised manuscript.

Extended cycling stability (200 cycles)

Adsorption–desorption cycling tests were extended to 200 consecutive cycles at a regeneration temperature of 100 °C using TGA (Supplementary Fig. 3). The CO₂ capture capacity remained stable throughout, increasing slightly by 2.28% from the first to the last cycle despite a modest overall mass decrease of 2.36%. These results substantially extend the 10-cycle lab-scale data presented in the original manuscript (Fig. 5g) and confirm the durability of the sorbent under repeated thermal cycling within the tested timeframe.

Oxidative aging

We acknowledge that oxidative degradation of amine-functionalized sorbents is a well-recognized challenge for long-term deployment, particularly under elevated temperatures in the presence of oxygen. Nezam et al.²⁴ characterized the autoxidation kinetics of PEI-impregnated mesoporous alumina and reported approximately 10% oxidative capacity loss when exposed to 5% O₂ at 125 °C for 500 min, proposing a lumped kinetic model with an activation energy of 105 kJ mol⁻¹. Wu et al.⁹ observed oxidative degradation in PEI-coated ceramic fibers, evidenced by the appearance of C=O bonds in Fourier transform infrared (FTIR) spectroscopy and decreased Brunauer-Emmett-Teller (BET) specific surface area after accelerated stability tests under high-temperature and high-humidity conditions. Although the application of hydrophobic binders (e.g., hydrophobic polystyrene-block-polybutadiene-block-polystyrene (SBS)) partially mitigated this degradation by reducing moisture access to the amine surface, the effect was limited and could not fully prevent amine oxidation. Recent reviews have further elucidated the degradation mechanisms and potential mitigation strategies³⁵.

Several factors in the present system are expected to reduce the rate of oxidative degradation compared to the conditions studied in these references. First, the regeneration temperature of 80–100 °C is substantially lower than the 125 °C condition under which significant oxidative loss was observed by Nezam et al.²⁴. Since autoxidation rates decrease exponentially with temperature, the lower operating temperature significantly reduces the oxidation rate. Second, the proposed CDCV system operates in a cyclic mode where Joule heating is applied only during brief regeneration intervals (15 min at 100 °C), limiting the cumulative high-temperature exposure of the amine sorbent. This contrasts with continuous-flow DAC systems where the sorbent may experience prolonged contact with oxygen at elevated temperatures.

Electrothermal performance stability

To evaluate whether oxidative aging or structural degradation of the carbon fiber substrate affects the electrothermal performance, the sorbent-coated filter was subjected to 100 consecutive Joule heating cycles at applied voltages of 4, 5, 6, and 7 V (Supplementary Fig. 18). At 4 V (~75 °C) and 5 V (~125 °C), the peak temperature remained stable with less than 3–5% variation over 100 cycles. At 6 V (~155 °C), a similar range of 3–5% variation was observed. At 7 V (~235 °C), which far exceeds the intended operating range and the amine thermal degradation threshold (~150 °C), approximately 15% reduction in peak temperature was observed, likely attributable to progressive oxidation of the carbon fiber surface at elevated temperatures. These results confirm that the electrothermal performance of the carbon fiber is well-maintained under the operating conditions employed in this study (DC 4–5 V, 80–100 °C), and that carbon fiber oxidation does not pose a practical concern within this temperature range.

Nevertheless, we recognize that the 200-cycle TGA tests conducted in this study do not fully replicate the cumulative oxidative stress expected over months to years of continuous building operation. The long-term oxidative stability of the sorbent under real-world conditions, including strategies such as oxygen-lean regeneration atmospheres, antioxidant additives, or periodic sorbent replacement, remains an important direction for future work. This point has been explicitly addressed in the revised manuscript.

Before:

Supplementary Fig. 9 presents the thermal response of carbon fiber with a single winding over 20 consecutive Joule heating cycles under applied voltages ranging from 4 V to 7 V. The results demonstrate a consistent increase in peak temperature with increasing voltage, while maintaining stable thermal profiles across all cycles. No significant degradation or fluctuation in temperature was observed, indicating that the carbon fiber exhibits excellent thermal durability and electrical reliability under repeated operation. These findings confirm the material's suitability for cyclic CO₂ desorption processes requiring stable and repeatable heat delivery.

After (Page 10):

Supplementary Fig. 9 presents the thermal response of carbon fiber with a single winding over **100** consecutive Joule heating cycles under applied voltages ranging from 4 V to 7 V, while maintaining stable thermal profiles across all cycles. **At lower voltages (4 V and 5 V), corresponding to peak temperatures up to approximately 100 °C, the carbon fiber exhibited excellent thermal stability with negligible performance variation across all cycles (< 3%). However, at higher voltages (6 V and 7 V), where peak temperatures exceeded 160°C, a gradual reduction in peak temperature of approximately 5-15% was observed over 100 cycles, likely attributable to cumulative thermal stress on the fiber and its binder at elevated operating temperatures. These findings indicate that the carbon fiber maintains reliable electrothermal performance within moderate temperature ranges, while performance degradation becomes non-negligible under repeated high-temperature operation.**

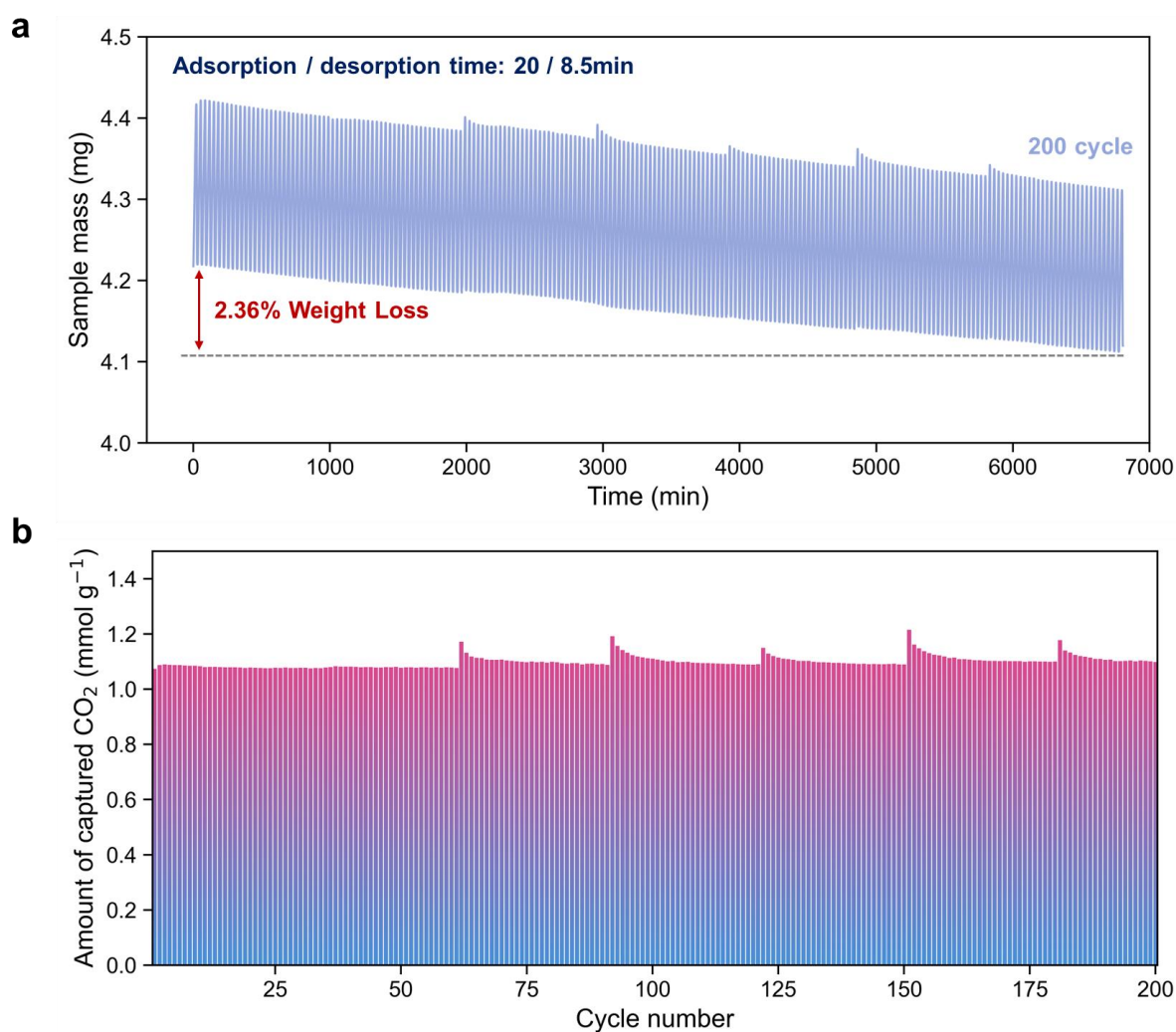
After (Page 27):

Additionally, oxidative degradation of amine functional groups under repeated thermal cycling in the presence of oxygen is a recognized challenge for long-term sorbent durability⁵¹⁻⁵⁴. In this study, the 200-cycle TGA test at 100 °C (Supplementary Fig. 3) showed that the overall sample mass decreased by only 2.36%, while the CO₂ capture capacity per unit mass remained stable with a slight increase of 2.28% from the first to the last cycle, and the moderate regeneration temperature (80–100 °C) is expected to substantially reduce the autoxidation rate compared to higher-temperature operations⁵¹. However, since vacuum-assisted regeneration is impractical for indoor environments due to noise, the introduction of inert purge gas (e.g., Ar, N₂) during Joule heating may serve as a viable strategy to suppress oxygen exposure and mitigate oxidative aging. The long-term oxidative stability under extended real-world operation warrants further investigation.

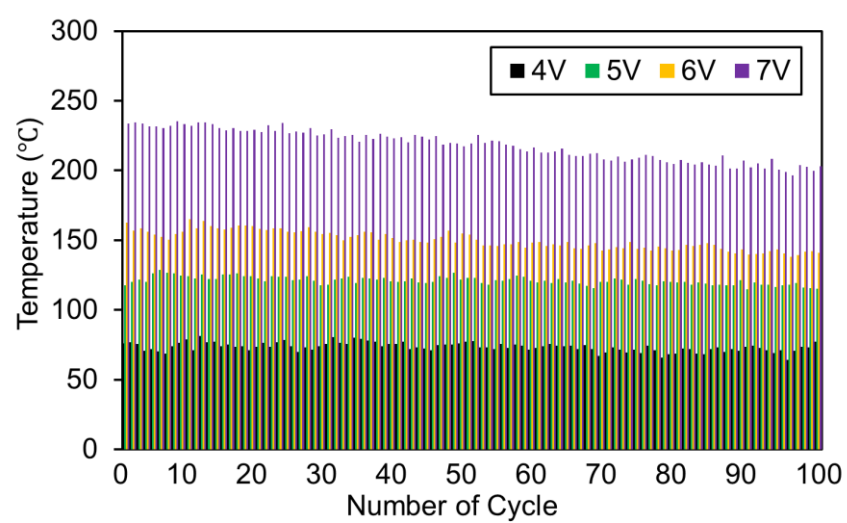
After (Page 32-33):

Long-term cyclic stability test

To evaluate the long-term durability of the sorbent under repeated thermal cycling, 200 consecutive partial adsorption–desorption cycles were performed using a simultaneous thermogravimetric analyzer (HITACHI, STA 200). Each cycle consisted of a 20 min adsorption phase at 25 °C under a 1,000 ppm CO₂/N₂ gas flow, followed by desorption via heating to 100 °C at a ramp rate of 10 °C min⁻¹ with a 1 min isothermal hold. Because the instrument is limited to 100 programmable temperature steps (approximately 30 cycles per run), the 200-cycle test was completed by performing seven sequential runs under identical conditions.



Supplementary Fig. 3. Long-term cyclic stability of the sorbent-coated carbon fiber filter over 200 adsorption-desorption cycles at regeneration temperature of 100 °C. (a) Thermogravimetric (TG) curve showing the sample mass variation across 200 cycles (b) Amount of captured CO₂ per cycle



Supplementary Fig. 9. Cyclic temperature stability of carbon fiber under different applied voltages.

10. From an application perspective, the manuscript should explain how the gas released during regeneration is handled.

Answer: We appreciate the reviewer's concern. The CDCV system proposed in this study operates by alternating between ventilation and CO₂ capture modes. During indoor air circulation, the CO₂ capture filter adsorbs CO₂ for a target duration determined operation logic. Subsequently, in the ventilation mode, regeneration process is conducted by joule heating, and the desorbed CO₂ is released to the outdoor environment. If this operational concept was not clearly conveyed, it reflects insufficient explanation in the manuscript. In response to the reviewer's comment, we have revised the manuscript to state that the CO₂ desorbed during the regeneration process is released outdoors. Thank you.

Before:

Here, we introduce a scalable CO₂ capture filter designed for direct integration with ventilation systems, enabling localized and energy-efficient regeneration through Joule heating method (Fig. 1).

After (Page 3-4):

Here, we introduce a scalable CO₂ capture filter designed for direct integration with ventilation systems, enabling localized and energy-efficient regeneration through Joule heating method (Fig. 1). **The proposed system achieves continuous CO₂ reduction through two distinct operational modes. In the internal circulation mode, an integrated filter removes indoor CO₂, while in the ventilation mode, the filter is regenerated via Joule heating. During regeneration, the desorbed CO₂ is discharged outdoors while fresh ambient air is introduced into the indoors, ensuring a continuous indoor carbon management cycle.**

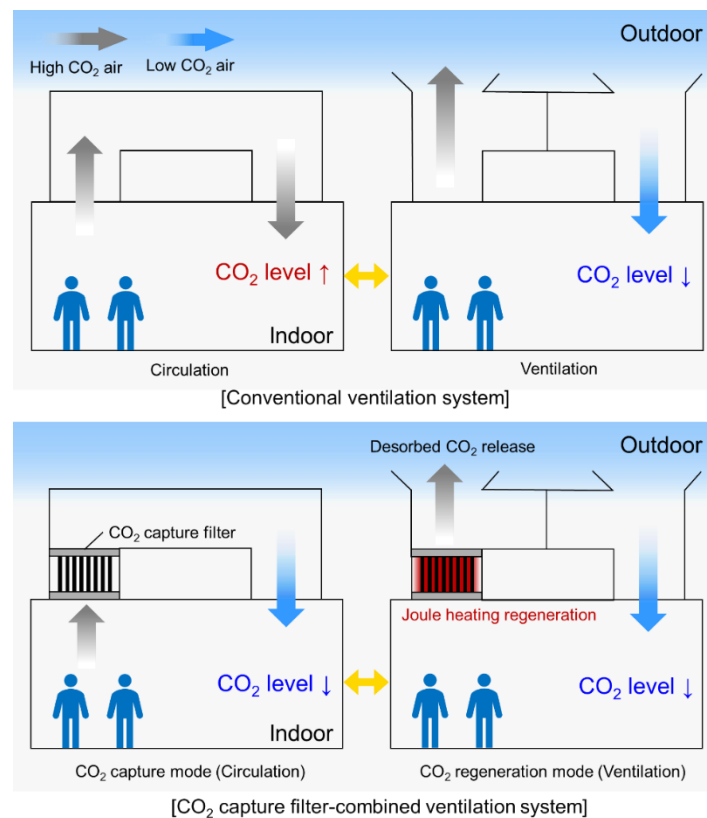


Fig. 1. Conceptual diagram of CO₂ capture filter-combined ventilation system

Responses to reviewers's comments

Reviewer #1 (Remarks to the Author):

The authors have addressed most of my concerns, but some revisions still need to be explained in detail.

1. Related to Q3: The authors mentioned that the closed system is not a practical ventilation system because it is difficult to accurately track low-concentration CO₂ capture behavior in an open system. Therefore, the authors should note this limitation in the revised manuscript to eliminate ambiguity for practical applications.

Answer: We appreciate the reviewer's insightful comment. To eliminate any ambiguity, we have added a discussion in the main text addressing the limitations inherent in the lab-scale experimental setup.

Before:

Breakthrough adsorption test is widely employed to evaluate the performance of CO₂ adsorbents at the lab-scale and serves as a standard performance metric. However, its applicability to actual ventilation systems is limited due to the high pressure drop, since these systems already incorporate pressure-inducing components such as High Efficiency Particulate Air (HEPA) filters and heat exchangers. In this study, the performance of the carbon fiber CO₂ capture filter was assessed using a batch-type acrylic chamber setup (Fig. 5a), which facilitates internal air circulation, continuous monitoring of CO₂ concentration, and simulates filter placement in realistic ventilation environments.

After (Page 12):

Breakthrough adsorption test is widely employed to evaluate the performance of CO₂ adsorbents at the lab-scale and serves as a standard performance metric. However, its applicability to actual ventilation systems is limited due to the high pressure drop, since these systems already incorporate pressure-inducing components such as High Efficiency Particulate Air (HEPA) filters and heat exchangers. In this study, the performance of the carbon fiber CO₂ capture filter was assessed using a batch-type acrylic chamber setup (Fig. 5a), which facilitates internal air circulation, continuous monitoring of CO₂ concentration, and simulates filter placement in realistic ventilation environments. It should be noted that this closed-loop recirculation system differs from an actual open ventilation system. A closed system was adopted because it enables accurate tracking of low-concentration CO₂ capture behavior and stable monitoring of cyclic performance, which is difficult to achieve in an open-flow system. Consequently, the absolute capture quantities and the temperature/humidity variations measured in this closed chamber should be interpreted as relative performance indicators rather than as direct predictors of in-situ behavior under actual open ventilation conditions, where desorbed CO₂ and moisture are discharged outdoors instead of accumulating within the test volume.

2. In addition, as authors mentioned, the dehumidification effect existed in the practical applications. However, the dehumidification effect may be useful in summer, but in practice, a humidification effect is needed in winter. In this case, I suggest that the authors discuss the practical applications across different seasons, taking into account the varying requirements for CO₂ concentration, temperature, and humidity.

Answer: We thank the reviewer for this valuable comment. We fully agree with the reviewer that the desired indoor conditions vary between seasons. Cooling and dehumidification are typically prioritized in summer, whereas heating and humidification become more important in winter. Because the regeneration step in our system releases the captured CO₂ along with the co-adsorbed water, the resulting exhaust carries both heat and moisture relative to the indoor air. This implies that the optimal way to dispose of the regeneration exhaust is not fixed but should change with the season.

In response, we have incorporated a discussion of how this exhaust could be managed differently across seasons. In summer, venting the desorbed CO₂ straight to the outdoors is beneficial, as the accompanying heat and moisture are unwanted indoors. In winter, by contrast, the same heat and moisture are valuable, so passing the exhaust through an energy recovery ventilator (ERV) would allow part of its sensible and latent energy to be reclaimed. We emphasize that this represents a conceptual operating scheme rather than a quantitatively verified outcome, as the realized benefit would vary with the system layout and ambient conditions; accordingly, we have framed it as a subject for future work. This addition, which accounts for the season-specific targets for indoor CO₂, temperature, and humidity, now appears in the revised manuscript. Thank you.

Before:

While the present study demonstrates a promising strategy for indoor CO₂ management, several limitations remain toward real-world adoption. The deep learning model was trained exclusively on simulated dataset, in which key parameters were intentionally simplified to isolate and evaluate the lab-scale filter performance, and has not been validated against real occupancy patterns or measured indoor CO₂ dynamics. The energy analysis and system-level simulation were also conducted under idealized boundary conditions, and system behavior under more complex and variable real-world scenarios remains to be verified.

After (Page 29):

While the present study demonstrates a promising strategy for indoor CO₂ management, several limitations remain toward real-world adoption. The deep learning model was trained exclusively on simulated dataset, in which key parameters were intentionally simplified to isolate and evaluate the lab-scale filter performance, and has not been validated against real occupancy patterns or measured indoor CO₂ dynamics. The energy analysis and system-level simulation were also conducted under idealized boundary conditions, and system behavior under more complex and variable real-world scenarios remains to be verified.

Practical deployment of the CDCV system, moreover, would need to account for season-dependent operating conditions. The preferred direction of indoor conditioning differs by season: in summer the indoor air is generally maintained cooler and drier than the outdoor air, whereas in winter it is maintained warmer and more humid. During regeneration, the desorbed CO₂ is released together with the co-adsorbed water, so the regeneration exhaust is relatively warm and humid compared with the captured indoor air; directly venting it outdoors is therefore advantageous in summer but discharges heat and moisture that are actually

desirable indoors in winter. This seasonal contrast suggests that the handling of the regeneration exhaust could itself be adapted to the season. One possible approach would be to discharge the desorbed CO₂ directly outdoors in summer, thereby rejecting both heat and moisture, while in winter routing the regeneration exhaust through an energy recovery ventilator (ERV) so that part of the sensible and latent heat in the outgoing stream is recovered. Such season-adaptive exhaust management may better reconcile CO₂ removal with seasonal temperature and humidity requirements; its quantitative benefit warrants future investigation.

Reviewer #2 (Remarks to the Author):

This manuscript presents an ambitious and interdisciplinary study combining materials development, Joule-heated CO₂ capture, structured filter design, ventilation modeling, and machine-learning-based optimization for indoor air quality control. The proposed CDCV system integrates amine-functionalized silica-coated carbon fiber filters with demand-controlled ventilation and deep learning-assisted operation. The topic is highly relevant to building energy efficiency and indoor environmental quality, and the experimental work at the material and filter scale is generally solid and well executed. However, in its current form, the manuscript does not yet meet the quality and validation level expected for the journal due to a clear gap between experimentally validated components and system-level claims, as well as limited benchmarking and uncertainty analysis.

The major comments and notes are as follows:

1. There is a strong mismatch between robust experimental results and system-level conclusions. The sorbent synthesis, characterization, Joule heating behavior, and lab-scale adsorption–desorption tests are convincing and demonstrate stable, reversible CO₂ capture with fast regeneration. However, the extension to building-scale performance is not experimentally validated. All claims related to energy savings and operational advantages of the CDCV system rely on simulation and optimization rather than HVAC or room-scale experiments, which significantly weakens the system-level conclusions.

Answer: Thank you for highlighting the distinction between the experimentally validated filter-scale results and the simulation-based system-level conclusions. We agree that the previous version did not sufficiently delineate the respective levels of validation and may therefore have overstated the extent to which the proposed CDCV system had been demonstrated under realistic building conditions. In response, we revised the manuscript to clearly distinguish experimentally validated filter-scale performance from simulation-based system-level projections. Material properties, Joule-heating behavior, adsorption–desorption kinetics, regeneration performance, and cyclic stability were experimentally evaluated, whereas building-scale CO₂ control and energy savings were assessed numerically. We therefore replaced expressions implying experimental validation with appropriately qualified terms and explicitly stated that building-scale validation remains necessary. We also clarified that the system model uses experimentally measured kinetics and regeneration-energy data as inputs, so the cyclic tests support the feasibility analysis without directly validating practical building operation.

Before:

Abstract

Carbon dioxide (CO₂) plays a key role in indoor air quality and is traditionally managed through ventilation, which often increases energy consumption. This work proposes a demand-controlled ventilation system integrated with a CO₂ filter (CDCV) to reduce both indoor CO₂ levels and ventilation-related energy use. The modular CO₂ capture filter was manufactured by spray-coating an amine-functionalized solid sorbent onto a carbon fiber substrate, enabling

rapid thermal regeneration via Joule heating within 15 min at 100 °C. System-scale operation was optimized using Differential Evolution and a deep neural network to adaptively coordinate filter regeneration and ventilation control under varying indoor conditions. Results show that the proposed system can lower energy loads by about 13.4–25% compared to conventional DCV systems, while maintaining indoor CO₂ at 600 ppm under various outdoor conditions. This work demonstrates a viable implementation pathway, validated through material characterization, lab-scale test, and system-level energy analysis.

After (Page 2):

Abstract

Carbon dioxide (CO₂) plays a key role in indoor air quality and is traditionally managed through ventilation, which often increases energy consumption. This work proposes a demand-controlled ventilation system integrated with a CO₂ filter (CDCV) to reduce both indoor CO₂ levels and ventilation-related energy use. The modular CO₂ capture filter was manufactured by spray-coating an amine-functionalized solid sorbent onto a carbon fiber substrate, enabling rapid thermal regeneration via Joule heating within 15 min at 100 °C. **System-scale operation was optimized using Differential Evolution, and a deep neural network was employed as a surrogate model to rapidly approximate the optimized control parameters across varying indoor conditions. Simulation-based analysis indicates the proposed system could lower energy loads by about 13.4–25% compared to conventional demand-controlled ventilation (DCV) systems, while maintaining indoor CO₂ at 600 ppm under various outdoor conditions. This work establishes an implementation pathway spanning material characterization, lab-scale tests, and model-based system-level analysis.**

Before:

To enhance flexibility, the filter employs a modular, cell-based architecture where both the number of cells and the fiber packing density per cell can be adjusted to match building ventilation demands. By integrating material-level analysis, lab-scale filter fabrication, and scenario-based indoor CO₂ reduction modeling, this work serves as a roadmap for evaluating the feasibility and practical validity of applying solid sorbents to building ventilation systems.

After (Page 4):

To enhance flexibility, the filter employs a modular, cell-based architecture where both the number of cells and the fiber packing density per cell can be adjusted to match building ventilation demands. ~~By integrating material-level analysis, lab-scale filter fabrication, and scenario-based indoor CO₂ reduction modeling, this work serves as a roadmap for evaluating the feasibility and practical validity of applying solid sorbents to building ventilation systems.~~ **The contribution of this work lies in assessing building-scale feasibility through simplified simulations grounded in lab-scale experimental results, rather than in reproducing actual indoor environments.**

Before:

Overall, the results confirm that typical partial regeneration ensures reliable, repeatable CO₂ capture with minimal energy input and thermal stress. This cyclic stability highlights the system's strong potential for integration into real-world indoor CO₂ management applications.

After (Page 15):

Overall, the results indicate that partial regeneration enables repeatable CO₂ capture with low energy input and thermal stress at the filter scale. The capture capacity and the adsorption/desorption kinetics obtained from these cyclic measurements serve as the experimental inputs to the system-level model described below. Herein, confirmation of the projected system-level performance under realistic building-scale conditions remains a necessary next step.

After (Page 18-19):

The system-level evaluation was conducted through numerical simulation rather than building-scale experiments, since controlled and repeatable variations in occupancy, room volume, and seasonal boundary conditions are difficult to achieve at full scale. All kinetic and energetic inputs to the model were taken from the lab-scale measurements: the adsorption and desorption rates were obtained from Avrami fits of the measured filter kinetics (Supplementary Notes 2 and 4), and the regeneration energy was derived from the experimentally determined temperature–power density relationship (Fig. 4f). The model therefore propagates experimentally measured filter performance to the system scale, while the ventilation control parameters (R_{occ} , R_{target}) follow established indoor-air-quality design standards.

Before:

Figure 8b summarizes four performance metrics: average deviation from the target CO₂ concentration, average ACH, total ventilation time, and air exchange volume. The DL-CDCV system achieved the lowest CO₂ deviation while maintaining comparable ventilation efficiency. Although the average-based CDCV system showed a slight reduction in ventilation time, it was less responsive to occupancy changes. These results demonstrate that the deep learning-based approach offers a more adaptive and responsive control strategy for maintaining indoor CO₂ stability under dynamic occupancy conditions. Using typical summer and winter weather data from South Korea as boundary conditions, the DL-CDCV system reduced ventilation energy consumption by 28.1% in summer and 28.3% in winter compared to the conventional DCV system (Supplementary Fig. 16). The detailed energy reduction calculation is provided in Supplementary Note 4.

After (Page 24):

Figure 8b summarizes four performance metrics: average deviation from the target CO₂ concentration, average ACH, total ventilation time, and air exchange volume. The DL-CDCV system achieved the lowest CO₂ deviation while maintaining comparable ventilation efficiency. Although the average-based CDCV system showed a slight reduction in ventilation time, it was less responsive to occupancy changes. **These simulation results indicate that the surrogate model reproduces the occupancy-responsive operation of the DE-optimized system, predicting the appropriate control parameters as occupancy varies and thereby emulating adaptive ventilation control across dynamic conditions.** In the simulation using typical summer and winter weather data from South Korea as boundary conditions, the DL-CDCV system reduced ventilation energy consumption by 28.1% in summer and 28.3% in winter relative to the conventional DCV system (Supplementary Fig. 16). The detailed energy reduction calculation is provided in Supplementary Note 4.

Before:

Case studies using real weather data demonstrated that the deep learning-assisted CDCV system achieved up to 28.3% energy savings compared to conventional ventilation. Feasibility analysis revealed two critical pathways to achieve energy parity at high CO₂ setpoints: increasing sorbent adsorption capacity by 1.38 times or reducing regeneration energy by 42.8%.

After (Page 32):

~~Case studies using real weather data demonstrated that the deep learning-assisted CDCV system achieved up to 28.3% energy savings compared to conventional ventilation.~~ **Simulation-based case studies using real weather data indicated that the deep learning-assisted CDCV system could achieve up to 28.3% energy savings relative to conventional system.** Feasibility analysis revealed two critical pathways to achieve energy parity at high CO₂ setpoints: increasing sorbent adsorption capacity by 1.38 times or reducing regeneration energy by 42.8%.

2. The energy and techno-economic analyses are conceptually reasonable but rely on simplified assumptions. The model does not capture key HVAC dynamics such as part-load efficiency, transient behavior, or humidity-driven control effects. While energy savings are shown in certain scenarios (notably winter), the system also increases energy demand in summer due to regeneration load. These trade-offs are not fully analyzed, and the sensitivity of results to assumptions is not sufficiently addressed, limiting confidence in the robustness of the reported savings.

Answer: We thank the reviewer for pointing out the limitations of the energy and techno-economic analyses and for emphasizing the need to better address the seasonal trade-offs and sensitivity of the reported results to the underlying assumptions. We agree that the previous manuscript did not sufficiently clarify the scope of the energy model or the conditions under which the CDCV system is advantageous. In response, we have revised the manuscript to explicitly state that the present energy formulation provides a first-order estimate of the ventilation thermal load based on the indoor–outdoor enthalpy difference and does not resolve detailed HVAC dynamics, including part-load efficiency, transient response, and humidity-driven control. We have also clarified that the heated and humidified regeneration air is assumed to be directly exhausted outdoors and that the regeneration energy is therefore treated as independent of season.

We have further expanded the discussion of the seasonal trade-off. The revised manuscript now explains that the CDCV system provides net energy savings under conditions with large ventilation loads, particularly in winter and at low CO₂ setpoints, because the reduction in ventilation thermal load exceeds the nearly constant regeneration demand. In contrast, under conditions with smaller indoor–outdoor enthalpy differences, such as summer operation at a high CO₂ setpoint, the avoided ventilation load is insufficient to offset the regeneration energy, resulting in an energy penalty. We therefore no longer present the CDCV system as universally energy-saving, but instead identify its benefit as dependent on the balance between the ventilation and regeneration loads. Furthermore, to address the reviewer’s concern regarding sensitivity, we also clarified that the analysis spans three CO₂ setpoints and both summer and winter conditions. Across this range, the qualitative trend remains consistent: the CDCV system becomes more favorable as the ventilation load increases and less favorable as the regeneration load becomes dominant. Although this does not replace a full parametric sensitivity analysis of all HVAC assumptions, it demonstrates that the reported trade-off is not attributable to a single

operating condition. Finally, the limitations section has been revised to state that the reported savings are condition-dependent first-order estimates and that further validation using dynamic HVAC models and real building operation is required. Thank you.

Before:

In these equations, $\bar{h}_{out}$ and h_{in} represent the average outdoor and target indoor air enthalpies, respectively, while $\bar{V}_{vent}$ denotes the average ventilation air volume, and ρ is the air density. The filter regeneration energy E_{regen} is defined as a product of the temperature-dependent power density $J(T)$ [$W\ m^{-2}$], the specific surface area per unit mass of the coated adsorbent $\frac{A_{fiber}}{m_{coated}}$ [$m^2\ g^{-1}$], the total filter mass m_{filter} [g], and the daily regeneration time t_{regen} [hr]. The detailed methodology for calculating these parameters and a full breakdown of the energy components are provided in Supplementary Note 5.

After (Page 26):

In these equations, $\bar{h}_{out}$ and h_{in} represent the average outdoor and target indoor air enthalpies, respectively, while $\bar{V}_{vent}$ denotes the average ventilation air volume, and ρ is the air density. The filter regeneration energy E_{regen} is defined as a product of the temperature-dependent power density $J(T)$ [$W\ m^{-2}$], the specific surface area per unit mass of the coated adsorbent $\frac{A_{fiber}}{m_{coated}}$ [$m^2\ g^{-1}$], the total filter mass m_{filter} [g], and the daily regeneration time t_{regen} [hr]. The detailed methodology for calculating these parameters and a full breakdown of the energy components are provided in Supplementary Note 5. **The present formulation estimates the ventilation thermal load from the indoor–outdoor enthalpy difference and does not resolve detailed HVAC dynamics such as part-load efficiency, transient response, or humidity-driven control. The heated and humidified air produced during regeneration is assumed to be exhausted directly outdoors, so the regeneration energy carries no seasonal scenario dependence. These simplifications apply identically to the reference DCV and the proposed CDCV systems, so that the absolute energy values represent first-order estimates while the relative comparison between the two systems remains meaningful. The net energy difference is thus governed by the ventilation load reduction and the added regeneration load, and the omitted HVAC dynamics would rescale both systems' loads similarly rather than reverse their ranking.**

Before:

Figure 9b presents the total energy demand of both DCV and CDCV systems under varying indoor CO₂ targets (600, 800, and 1,000 ppm) across summer and winter seasons. For the CDCV system, energy calculations were based on a 200 g sorbent-coated filter, with regeneration energy estimated using desorption duration and the experimentally derived temperature–power density relationship shown in Fig. 4f. The CDCV system consistently reduces ventilation-related thermal loads across all scenarios by lowering ventilation rates through intermittent CO₂ capture. However, the added regeneration energy, indicated by yellow markers, significantly affects total energy consumption. In winter, the CDCV system achieves approximately 25.0% net energy savings at a 600 ppm target due to the large enthalpy difference between indoor and outdoor air, highlighting its potential under strict CO₂ control. As the CO₂ setpoint increases, the relative energy benefit decreases because ventilation demand

drops while regeneration energy remains stable, reducing net savings. Conversely, in summer at 1,000 ppm, the CDCV system consumes about 34.4% more total energy than the DCV system. To address this limitation, further analysis was conducted to identify system improvements needed to reduce energy consumption under high-load conditions.

After (Page 27):

Figure 9b presents the total energy demand of both DCV and CDCV systems under varying indoor CO₂ targets (600, 800, and 1,000 ppm) across summer and winter seasons. For the CDCV system, energy calculations were based on a 200 g sorbent-coated filter, with regeneration energy estimated using desorption duration and the experimentally derived temperature–power density relationship shown in Fig. 4f. The CDCV system consistently reduces ventilation-related thermal loads across all scenarios by lowering ventilation rates through intermittent CO₂ capture. However, the added regeneration energy, indicated by yellow markers, significantly affects total energy consumption. In winter, the CDCV system achieves approximately 25.0% net energy savings at a 600 ppm target due to the large enthalpy difference between indoor and outdoor air, highlighting its potential under strict CO₂ control. As the CO₂ setpoint increases, the relative energy benefit decreases because ventilation demand drops while regeneration energy remains stable, reducing net savings. Conversely, in summer at 1,000 ppm, the CDCV system consumes about 34.4% more total energy than the DCV system. This asymmetry arises because the larger winter savings reflect the inherently greater indoor–outdoor enthalpy difference in winter, whereas in summer the smaller enthalpy difference provides limited ventilation savings against a nearly constant regeneration load. The CDCV system is therefore advantageous under large ventilation loads (low CO₂ setpoints and high enthalpy differences, notably winter) and incurs a penalty in the opposite regime. Notably, this trade-off holds consistently across all CO₂ setpoints and both seasons examined, indicating that the qualitative outcome is governed by the balance between ventilation and regeneration loads rather than by any single assumed condition. A further analysis was therefore conducted to identify the system improvements needed to reduce energy consumption in the regime where the regeneration load dominates.

Before:

While the present study demonstrates a promising strategy for indoor CO₂ management, several limitations remain toward real-world adoption. The deep learning model was trained exclusively on simulated dataset, in which key parameters were intentionally simplified to isolate and evaluate the lab-scale filter performance, and has not been validated against real occupancy patterns or measured indoor CO₂ dynamics. The energy analysis and system-level simulation were also conducted under idealized boundary conditions, and system behavior under more complex and variable real-world scenarios remains to be verified.

After (Page 29):

While the present study demonstrates a promising strategy for indoor CO₂ management, several limitations remain toward real-world adoption. The deep learning model was trained exclusively on simulated dataset, in which key parameters were intentionally simplified to isolate and evaluate the lab-scale filter performance, and has not been validated against real occupancy patterns or measured indoor CO₂ dynamics. ~~The energy analysis and system-level simulation were also conducted under idealized boundary conditions, and system behavior under more complex and variable real world scenarios remains to be verified.~~ These

simplifications include a well-mixed single-zone air model, deterministic occupancy profiles, and an idealized control response. Such idealizations render the indoor environment more controllable than a real space, so the CO₂ concentration control and ventilation-energy savings reported here are expected to represent an upper bound relative to real indoor conditions. The network thus serves as a machine-learning surrogate model that emulates the system's operation under varying occupancy-driven loads within a simulated environment. Extension of the surrogate to larger building scales also remains for future work, since the interactions among occupancy, indoor volume, and sorbent capacity reshape the input–output relationship beyond the present design ranges and would require additional optimization data for retraining. The energy analysis and system-level simulation were also conducted under idealized boundary conditions, so the reported savings are best interpreted as condition-dependent first-order estimates, with season-specific operation identified as a route to further improvement. System behavior under more complex and variable real-world scenarios accordingly remains to be verified.

3. The machine learning framework lacks sufficient methodological detail and validation. The neural network is trained solely on simulation data, with no real-world validation against occupancy or CO₂ measurements. Key details such as dataset size, generalization ability, and uncertainty quantification are missing. In its current form, the ML model should be viewed as a surrogate model rather than a validated control strategy.

Answer: We sincerely appreciate the reviewer's constructive suggestion. We fully agree that, in the absence of real-world validation against measured occupancy or CO₂ data, the neural network is most accurately described as a surrogate model rather than a validated control strategy. Accordingly, we have revised the manuscript throughout to reframe the FCDNN as a surrogate model that rapidly approximates the DE-optimized control parameters, and we have removed expressions that implied a validated real-time controller.

We have also supplemented the methodological details requested by the reviewer, addressing each of the three items in turn.

First, regarding dataset size, the FCDNN surrogate was trained on a dataset of 22,400 DE-optimized cases generated across the five input variables, split into training, validation, and test sets at a 7:2:1 ratio. This information is now stated explicitly in the revised manuscript.

Second, regarding generalization ability, the surrogate was first assessed on the held-out test set, yielding normalized MAE values of 2.5%, 4.72%, and 3.81% for η_{des} , R_{target} , and R_{occ} , respectively. Generalization beyond a single train–test partition was then examined through five-fold cross-validation on the same dataset. The data were randomly divided into five folds; in each iteration, one fold served as the test set while the remaining four folds were used for training and validation, with normalization statistics recomputed and the network re-initialized within each fold to prevent information leakage across partitions.

Third, regarding uncertainty quantification, the predictive uncertainty of the surrogate was quantified using the deep ensemble method of Lakshminarayanan et al., a widely adopted approach cited more than 10,000 times. Five probabilistic FCDNNs, each producing a predictive mean and variance, were trained independently under the negative log-likelihood criterion, and the ensemble predictive distribution was evaluated through reliability diagrams and the relationship between predictive standard deviation and prediction error. The methodology and results are provided in revised manuscript and SI.

Finally, we clarify in the revised text that these analyses quantify how closely and how reliably the surrogate reproduces the DE optimizer, and do not constitute validation against real indoor environments, which remains future work. The corresponding changes are reflected in the manuscript as detailed below. Thank you.

[Reference work] Lakshminarayanan, B., Pritzel, A., & Blundell, C. (2017). Simple and scalable predictive uncertainty estimation using deep ensembles. *Advances in neural information processing systems*, 30.

Before:

Abstract

Carbon dioxide (CO₂) plays a key role in indoor air quality and is traditionally managed through ventilation, which often increases energy consumption. This work proposes a demand-controlled ventilation system integrated with a CO₂ filter (CDCV) to reduce both indoor CO₂ levels and ventilation-related energy use. The modular CO₂ capture filter was manufactured by spray-coating an amine-functionalized solid sorbent onto a carbon fiber substrate, enabling rapid thermal regeneration via Joule heating within 15 min at 100 °C. System-scale operation was optimized using Differential Evolution and a deep neural network to adaptively coordinate filter regeneration and ventilation control under varying indoor conditions. Results show that the proposed system can lower energy loads by about 13.4–25% compared to conventional DCV systems, while maintaining indoor CO₂ at 600 ppm under various outdoor conditions. This work demonstrates a viable implementation pathway, validated through material characterization, lab-scale test, and system-level energy analysis.

After (Page 2):

Abstract

Carbon dioxide (CO₂) plays a key role in indoor air quality and is traditionally managed through ventilation, which often increases energy consumption. This work proposes a demand-controlled ventilation system integrated with a CO₂ filter (CDCV) to reduce both indoor CO₂ levels and ventilation-related energy use. The modular CO₂ capture filter was manufactured by spray-coating an amine-functionalized solid sorbent onto a carbon fiber substrate, enabling rapid thermal regeneration via Joule heating within 15 min at 100 °C. **System-scale operation was optimized using Differential Evolution, and a deep neural network was employed as a surrogate model to rapidly approximate the optimized control parameters across varying indoor conditions. Simulation-based analysis indicates the proposed system could lower energy loads by about 13.4–25% compared to conventional demand-controlled ventilation (DCV) systems, while maintaining indoor CO₂ at 600 ppm under various outdoor conditions. This work establishes an implementation pathway spanning material characterization, lab-scale tests, and model-based system-level analysis.**

Before:

Figure 6b presents the overall research framework for scenario-based indoor application studies, encompassing both optimization and deep learning phases. Five key indoor parameters—occupancy (1–4 persons), adsorbent mass (25–500 g), indoor volume (200–400 m³), target CO₂ concentration (600–1,200 ppm), and initial concentration (600–1,200 ppm)—were systematically

varied to develop operational strategies that maintain the desired indoor CO₂ levels.

After (Page 19):

Figure 6b presents the overall research framework for scenario-based indoor application studies, encompassing both optimization and deep learning phases. Five key indoor parameters—occupancy (1–4 persons), adsorbent mass (25–500 g), indoor volume (200–400 m³), target CO₂ concentration (600–1,200 ppm), and initial concentration (600–1,200 ppm)—were systematically varied to develop operational strategies that maintain the desired indoor CO₂ levels. **Systematic combination of these input variables yielded a total of 22,400 cases, for each of which the optimal control parameters were obtained by DE optimization to construct the dataset used for surrogate model training.**

Before:

Deep learning-based indoor application case study

A predictive framework linking system inputs to optimal control parameters was developed using a FCDNN. The model was trained on optimized datasets to estimate η_{des} , R_{target} , and R_{occ} based on five key indoor variables. Bayesian optimization was applied to identify the optimal network architecture and hyperparameters, minimizing the combined MAE and RMSE. The trained model achieved normalized MAE values of 2.5%, 4.72%, and 3.81% for η_{des} , R_{target} , and R_{occ} , respectively (Supplementary Table 4). Scatter plots in Supplementary Fig. 16a, 16c, and 16e show strong agreement between predicted and actual values, demonstrating the model's ability to capture nonlinear relationships. Permutation-based feature importance analysis revealed that occupancy was the most influential factor for predicting R_{target} (26.72%) and η_{des} (12.75%), while adsorbent mass and C_{target} had significant effects on R_{occ} . Indoor volume showed minimal influence across all outputs. These findings are summarized in radar plots (Supplementary Fig. 16b, 16d, and 16f) and detailed in Supplementary Table 4, providing a comprehensive view of input feature impacts on model performance.

After (Page 23):

Deep learning-based indoor application case study

A surrogate model linking system inputs to the DE-optimized control parameters was developed using a FCDNN. The model was trained on the optimized datasets to approximate η_{des} , R_{target} , and R_{occ} based on five key indoor variables. Bayesian optimization was applied to identify the optimal network architecture and hyperparameters, minimizing the combined MAE and RMSE. The trained model achieved normalized MAE values of 2.5%, 4.72%, and 3.81% for η_{des} , R_{target} , and R_{occ} , respectively (Supplementary Table 4). Scatter plots in Supplementary Fig. 16a, 16c, and 16e show strong agreement between predicted and actual values, **confirming that the surrogate reproduces the optimized parameters with high fidelity.** Herein, permutation-based feature importance analysis revealed that occupancy was the most influential factor for predicting R_{target} (26.72%) and η_{des} (12.75%), while adsorbent mass and C_{target} had significant effects on R_{occ} . Indoor volume showed minimal influence across all outputs. These findings are summarized in radar plots (Supplementary Fig. 16b, 16d, and 16f) and detailed in Supplementary Table 4, providing a comprehensive view of input feature impacts on model performance.

Furthermore, the generalization ability of the surrogate was verified through five-fold cross-validation, which yielded consistent normalized MAE values of $2.76 \pm 0.24\%$, $5.23 \pm 0.23\%$, and $3.95 \pm 0.13\%$ across folds for η_{des} , R_{target} , and R_{occ} , respectively (Supplementary Note 4, Supplementary Table 5); the low fold-to-fold variation confirms that the surrogate accuracy is not specific to any single data partition. While cross-validation establishes the average accuracy of the surrogate, it does not indicate how much confidence should be placed in any individual prediction. The predictive uncertainty of the surrogate was therefore quantified using a deep ensemble of five probabilistic FCDNNs, each trained to output a predictive mean and variance under the negative log-likelihood criterion (Supplementary Note 4)⁴⁹. The predictive standard deviation was strongly rank-correlated with the absolute prediction error ($\rho = 0.87\text{--}0.94$ across the outputs), and the most-confident half of the test set exhibited only 3–9% of the overall RMSE (Supplementary Fig. 17b, Supplementary Table 6). The prediction intervals were conservative, covering more observations than their nominal level and thereby avoiding overconfident estimates (Supplementary Fig. 17a).

After (SI Page 21):

Five-fold cross-validation

The generalization ability of the surrogate model was examined through five-fold cross-validation. The dataset of 22,400 DE-optimized cases was randomly partitioned into five folds. In each iteration, one fold served as the test set while the remaining four folds were used for model training and validation. The per-output cross-validation error was quantified as the mean normalized MAE across folds, defined as:

$$\overline{nMAE_j} = \frac{1}{k} \sum_{k=1}^k \frac{MAE_{j,k}}{|\overline{y_j}|_k} \times 100, \quad k = 5 \quad (\text{S18})$$

where j indexes the output variable (η_{des} , R_{target} , R_{occ}), k indexes the fold, $MAE_{j,k}$ is the mean absolute error on test fold k , and $|\overline{y_j}|_k$ is the mean of the absolute actual values in that fold. Normalization statistics were recomputed from the training portion of each fold, and the network was re-initialized for every fold, so that no information leaked across partitions.

Uncertainty quantification of the FCDNN model using deep ensembles

The FCDNN model is trained on deterministic outputs of the DE optimization, so conventional uncertainty analysis based on measurement noise is not directly applicable; the relevant uncertainty is instead the predictive uncertainty of the surrogate itself; the degree of confidence associated with each predicted control parameter. This uncertainty was quantified using the deep ensemble method of Lakshminarayanan et al.¹, which provides predictive distributions without modification of the standard training pipeline and without the computational burden of Bayesian neural networks.

Each ensemble member is a probabilistic variant of the baseline FCDNN, sharing the identical backbone architecture (four hidden layers of 128 neurons with ReLU activation) but producing two outputs per target instead of one. Each member was trained by minimizing the Gaussian negative log-likelihood (NLL):

$$-\log p_{\theta}(y|x) = \frac{1}{2} \log \sigma_{\theta}^2(x) + \frac{(y - \mu_{\theta}(x))^2}{2\sigma_{\theta}^2(x)} + \text{constant} \quad (\text{S19})$$

where x is the vector of the five input variables, y is the DE-optimized target value, $\mu_{\theta}(x)$ is the predictive mean, $\sigma_{\theta}^2(x)$ is the predictive variance, and θ denotes the network parameters. The first term penalizes overestimated variance, while the second term penalizes prediction errors more heavily when the network claims high confidence (small σ_{θ}^2); their balance makes a proper scoring rule that rewards calibrated predictive distributions. Positivity of $\sigma_{\theta}^2(x)$ was enforced through a softplus transformation of the corresponding network output. An ensemble of $M = 5$ members was trained independently on the identical training partition (70% of the dataset, with the same 7:2:1 train/validation/test split used for the baseline model), with diversity induced solely through random parameter initialization and random shuffling of mini-batches. Training employed the Adam optimizer (learning rate 10^{-3} , batch size 16) with early stopping on the validation NLL.

The predictive distribution of the ensemble was approximated as a uniformly weighted Gaussian mixture. Its predictive mean was calculated as

$$\mu_*(x) = \frac{1}{M} \int_{m=1}^M \mu_{\theta m}(x) \quad (\text{S20})$$

while the predictive variance was estimated as

$$\sigma_*^2(x) = \frac{1}{M} \int_{m=1}^M (\sigma_{\theta m}^2(x) + \mu_{\theta m}^2(x)) - \mu_*^2(x) \quad (\text{S21})$$

where $\mu_{\theta m}(x)$ and $\sigma_{\theta m}^2(x)$ are the predictive mean and variance of the m -th ensemble member, respectively. The ensemble mean, $\mu_*(x)$ was used as the final surrogate prediction, while the predictive variance, $\sigma_*^2(x)$, served as the uncertainty estimate. The predictive variance naturally reflects both the predictive variances of the individual ensemble members and the disagreement among their predictive means. Consequently, larger values of σ_*^2 indicate lower confidence in the surrogate prediction and are expected to occur particularly for operating conditions that deviate from the distribution represented in the training dataset.

The uncertainty estimates were evaluated on the held-out test set in two complementary ways. First, calibration was assessed through reliability diagrams: for central prediction intervals of nominal coverage 10–90% constructed from μ_* and σ_* , the observed fraction of test observations falling within each interval was computed, with a well-calibrated model lying on the diagonal. Second, the relationship between the predictive standard deviation and the absolute prediction error was examined by ranking test samples by σ_* and computing the RMSE of progressively larger most-confident subsets, together with the Spearman rank correlation between σ_* and the absolute error. The results of these evaluations are presented in Supplementary Fig. 17 and discussed in the main text.

Supplementary Table 5. Five-fold cross-validation results of the FCDNN model. Values are normalized MAE (%), reported for each fold and as mean $\pm$ s.d..

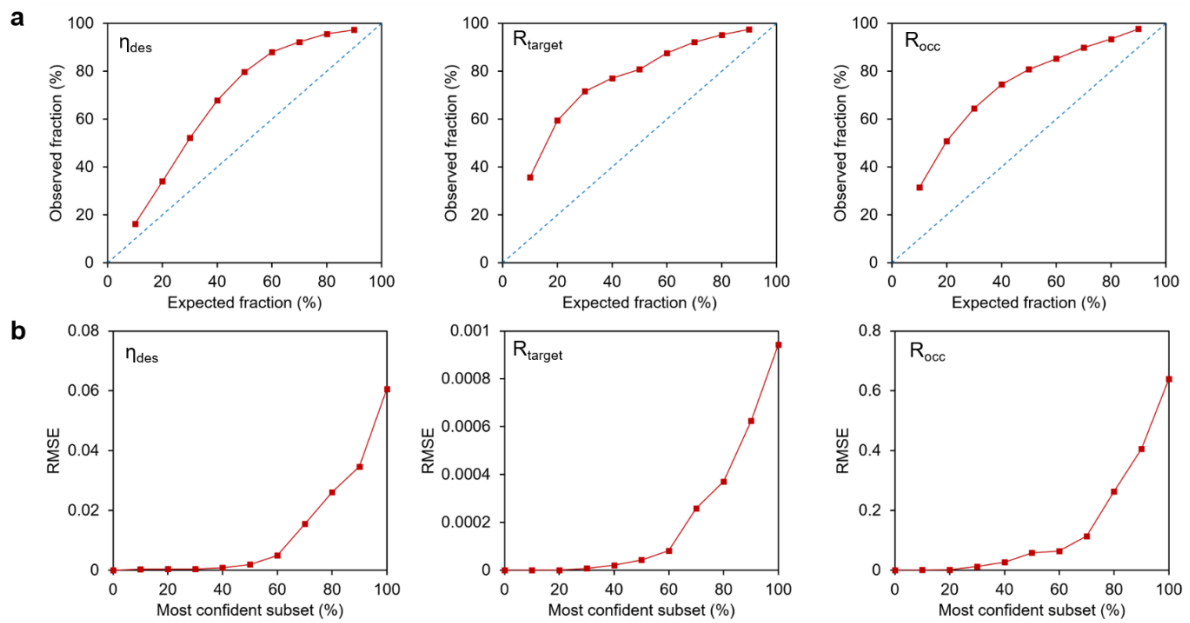
Fold	$\eta_{\text{des.}}$	R_{target}	R_{occ}
1	2.52	5.05	3.92
2	2.58	5.21	3.80
3	2.88	5.08	3.98

4	3.10	5.19	3.89
5	2.72	5.61	4.15
Mean $\pm$ s.d.	2.76 ± 0.24	5.23 ± 0.23	3.95 ± 0.13

* s.d.: Standard deviation

Supplementary Table 6. Predictive performance and uncertainty of the deep-ensemble surrogate model on the held-out test set.

Output	nMAE (%)	nRMSE (%)	NLL	Mean σ	$\rho(\sigma, \text{error})$
η_{des}	3.15	7.12	-3.45	0.0428	0.87
R_{target}	5.52	12.04	-7.60	6.09×10^{-4}	0.94
R_{occ}	3.98	8.81	-0.73	0.435	0.88



Supplementary Fig. 17. Predictive uncertainty of the FCDNN surrogate model quantified by deep ensembles. (a) Reliability diagrams. (b) RMSE of the most-confident test subsets, ranked by predictive standard deviation.

Before:

A case study was conducted to compare the performance of the Deep Learning-assisted CDCV (DL-CDCV) system against conventional DCV and average occupancy-based CDCV systems under a dynamic 24-hour occupancy scenario in a 300 m³ space with a fixed CO₂ target of 800 ppm. Fig. 8a presents time-series data for indoor CO₂ concentration, air change rate (ACH), and key control parameters. All systems maintained CO₂ concentrations within ± 200

ppm of the target; however, DL-CDCV demonstrated tighter control, especially during occupancy transitions. The ACH profiles reveal that DL-CDCV reduced ventilation demand during low-occupancy periods by actively leveraging CO₂ capture, while also responding more rapidly to occupancy changes. Control parameters (R_{occ} , R_{target} , η_{des}) were adaptively adjusted in real time, improving control precision under varying conditions.

Figure 8b summarizes four performance metrics: average deviation from the target CO₂ concentration, average ACH, total ventilation time, and air exchange volume. The DL-CDCV system achieved the lowest CO₂ deviation while maintaining comparable ventilation efficiency. Although the average-based CDCV system showed a slight reduction in ventilation time, it was less responsive to occupancy changes. These results demonstrate that the deep learning-based approach offers a more adaptive and responsive control strategy for maintaining indoor CO₂ stability under dynamic occupancy conditions. In the simulation using typical summer and winter weather data from South Korea as boundary conditions, the DL-CDCV system reduced modeled ventilation energy consumption by 28.1% in summer and 28.3% in winter relative to the conventional DCV system (Supplementary Fig. 16). The detailed energy reduction calculation is provided in Supplementary Note 4.

After (Page 23-24):

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Figure 8b summarizes four performance metrics: average deviation from the target CO₂ concentration, average ACH, total ventilation time, and air exchange volume. The DL-CDCV system achieved the lowest CO₂ deviation while maintaining comparable ventilation efficiency. Although the average-based CDCV system showed a slight reduction in ventilation time, it was less responsive to occupancy changes. These simulation results indicate that the surrogate model reproduces the occupancy-responsive operation of the DE-optimized system, predicting the appropriate control parameters as occupancy varies and thereby emulating adaptive ventilation control across dynamic conditions. In the simulation using typical summer and winter weather data from South Korea as boundary conditions, the DL-CDCV system reduced ventilation energy consumption by 28.1% in summer and 28.3% in winter relative to the conventional DCV system (Supplementary Fig. 16). The detailed energy reduction calculation is provided in Supplementary Note 4.

Before:

While the present study demonstrates a promising strategy for indoor CO₂ management, several limitations remain toward real-world adoption. The deep learning model was trained exclusively on simulated dataset, in which key parameters were intentionally simplified to

isolate and evaluate the lab-scale filter performance, and has not been validated against real occupancy patterns or measured indoor CO₂ dynamics. The energy analysis and system-level simulation were also conducted under idealized boundary conditions, and system behavior under more complex and variable real-world scenarios remains to be verified.

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Before:

Discussion

In summary, this study presents a comprehensive framework for integrating CO₂ capture filter into demand-controlled ventilation (DCV) systems, addressing limitations of conventional indoor air quality management. At the material level, a regenerable amine-functionalized silica was developed and incorporated into a carbon fiber-based filter, enabling localized thermal desorption via Joule heating. At the system level, a simulation platform assessed the performance of the CO₂ filter-integrated DCV (CDCV) system under varied occupancy and environmental conditions. Differential Evolution optimization identified key control parameters to minimize ventilation load while maintaining indoor CO₂ within acceptable limits. To enhance adaptability, a deep neural network was trained on large-scale simulation data for real-time control based on occupancy feedback.

After (Page 31-32):

Discussion

In summary, this study presents a comprehensive framework for integrating CO₂ capture filter into demand-controlled ventilation (DCV) systems, addressing limitations of conventional indoor air quality management. At the material level, a regenerable amine-functionalized silica was developed and incorporated into a carbon fiber-based filter, enabling localized thermal

desorption via Joule heating. At the system level, a simulation platform assessed the performance of the CO₂ filter-integrated DCV (CDCV) system under varied occupancy and environmental conditions. Differential Evolution optimization identified key control parameters to minimize ventilation load while maintaining indoor CO₂ within acceptable limits. To enhance adaptability, a deep neural network was trained as a surrogate model on large-scale simulation data to approximate the optimized control parameters from occupancy feedback. Simulation-based case studies using real weather data indicated that the deep learning-assisted CDCV system could achieve up to 28.3% energy savings relative to conventional system.

4. The indoor CO₂ system model is based on strong simplifications, including well-mixed air assumptions, deterministic occupancy, and idealized control response. These assumptions may lead to overestimation of control performance and energy savings. Their implications should be more clearly acknowledged and discussed.

Answer: We thank the reviewer for this valuable comment. We agree that, although these simplifications were adopted for specific reasons, they inevitably affect the assessment of the filter's real-world effectiveness through some degree of overestimation.

The lab-scale experiments were conducted in a tightly sealed, closed-loop chamber, and the simulation was therefore configured to reproduce the same environment. Without system-level validation, introducing the added complexity of a real space could distort the purpose of the simulation; the simplifying assumptions were instead chosen to evaluate the filter's performance transparently. We recognize, however, that these same assumptions may overstate the achievable performance. This study aims to evaluate the applicability of a newly introduced lab-scale CO₂ filter, and adding further modeling detail that has not been experimentally verified could obscure the specific effect of this new component. We therefore adopted a level of detail that isolates the CO₂ reduction and thermal-load effects of the filter, which we believe is the more informative basis for a first assessment. To remove any ambiguity, we have revised the manuscript to state explicitly that the well-mixed air, deterministic occupancy, and idealized control assumptions cause the filter's CO₂ concentration control and ventilation-energy savings to be evaluated more favorably than would be expected under real indoor conditions. We appreciate the reviewer's comment, which has helped us present the scope and limitations of the model more transparently.

Before:

In the field of DCV, simplified mass balance equations are commonly employed to calculate CO₂ concentration ($C(t)$) and CO₂ generation ($G(t)$) within a single zone

After (Page 17):

In the field of DCV, simplified mass balance equations are commonly employed to calculate CO₂ concentration ($C(t)$) and CO₂ generation ($G(t)$) within a single zone³². This formulation assumes a well-mixed indoor volume with spatially uniform CO₂ concentration, providing a tractable basis for control analysis while omitting local spatial gradients.

Before:

While the present study demonstrates a promising strategy for indoor CO₂ management, several limitations remain toward real-world adoption. The deep learning model was trained exclusively on simulated dataset, in which key parameters were intentionally simplified to isolate and evaluate the lab-scale filter performance, and has not been validated against real occupancy patterns or measured indoor CO₂ dynamics.

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While the present study demonstrates a promising strategy for indoor CO₂ management, several limitations remain toward real-world adoption. The deep learning model was trained exclusively on simulated dataset, in which key parameters were intentionally simplified to isolate and evaluate the lab-scale filter performance, and has not been validated against real occupancy patterns or measured indoor CO₂ dynamics. **These simplifications include a well-mixed single-zone air model, deterministic occupancy profiles, and an idealized control response. Such idealizations render the indoor environment more controllable than a real space, so the CO₂ concentration control and ventilation-energy savings reported here are expected to represent an upper bound relative to real indoor conditions.**

5. Benchmarking against state-of-the-art materials and HVAC-integrated CO₂ capture systems is insufficient. The adsorption capacity is moderate compared to leading amine-based and structured sorbent systems, suggesting that the main novelty lies in system integration and regeneration strategy rather than material performance. This distinction should be made clearer.

Answer: We sincerely thank the reviewer for this insightful comment, and we fully agree with the reviewer's assessment. The intrinsic CO₂ adsorption capacity of the present sorbent is indeed moderate compared with leading amine-based sorbents, and the principal contribution of this work lies in the device-level implementation and system-level integration rather than in maximizing material-level capacity. To make this distinction explicit and to strengthen the benchmarking, we have revised manuscript, Supplementary Table 7, and Supplementary Note 8 accordingly.

First, to make the locus of novelty directly visible, we have added a new "Demonstration level" column (Material / Device / System) to Supplementary Table 7 and revised its title accordingly. Under this classification, This Work is the only entry demonstrated at the system level, i.e., a capture device integrated and operated within a demand-controlled ventilation framework under deep-learning-based control.

Second, the table that was previously restricted to Joule-heating-based electrothermal adsorbents has been expanded to incorporate state-of-the-art amine-based sorbents evaluated under low-concentration (400 ppm) conditions relevant to our application. These include TEPA- and PEI-impregnated mesoporous silica (2.30–2.57 mmol g⁻¹), which exhibit substantially higher equilibrium capacities than the present sorbent (1.84 mmol g⁻¹ at the powder scale under 1,000 ppm). We have also included Lewatit VP OC 1065, a widely used amine-functionalized resin with well-documented low-concentration adsorption data and process-relevant material properties; although its capacity at 400 ppm (approximately 0.95–1.1 mmol g⁻¹ under dry conditions) is comparable to the present sorbent, it provides a practical reference point against a commercially deployed DAC material. A structured PEI/mesoporous-silica monolith³ demonstrated at the device level has likewise been added, which relies on steam-assisted regeneration impractical for occupied indoor spaces. In addition, a recently

reported pyrazine-functionalized Co-MOF has been added as a high-surface-area benchmark. We note that this MOF is a powder rather than a structured sorbent; MOFs are widely recognized for their exceptionally high CO₂ uptake at elevated concentrations owing to their very large BET surface areas, but this advantage does not carry over to the low partial pressures relevant to indoor CO₂ management: the pyrazine-Co-MOF adsorbs 5.7 mmol g⁻¹ at 10,000 ppm but only 1.36 mmol g⁻¹ at 400 ppm. This concentration dependence, now made explicit in the table, reinforces that high intrinsic capacity measured at elevated concentration is not a reliable indicator of trace-CO₂ capture performance under indoor-relevant conditions.

Third, a comparison of capacity alone understates the operational trade-offs relevant to indoor deployment. The highest-capacity amine sorbents in the expanded table (e.g., TEPA-impregnated silica) suffer pronounced capacity loss upon extended cycling (up to ~29% over 50 cycles, accompanied by ~55% amine loss through volatilization), whereas the present filter retains full capacity over 200 cycles. This durability, together with the vacuum-free moderate-temperature regeneration, underpins the suitability of the proposed system for prolonged indoor operation, even where its intrinsic capacity is moderate.

Before

A systematic comparison with recently reported Joule-heating-based CO₂ capture systems is provided in Supplementary Table 7 and Supplementary Note 8. Lee et al.⁴ achieved 95% desorption in 10 min at 110 °C under 0.3 bar vacuum using PEI-impregnated mesoporous silica coated on carbon fibers for DAC. Lee et al.⁵ developed silver nanocomposite-coated zeolite fibers with a partial vacuum-assisted e-TVSA cycle for DAC. Wu et al.⁶ proposed a carbon nanofiber-based DAC air filter for building ventilation, though requiring off-site regeneration with filter replacement every two days. All three studies target DAC at 400 ppm, whereas the present work applies Joule-heating-based regeneration to indoor CO₂ at 1,000-2,000 ppm. The proposed filter achieves vacuum-free desorption (95% within 15 min at 100 °C), enabled by nonporous silica nanoparticles that minimize intra-particle diffusion resistance and a thin sorbent layer (14.7–46.1 μm) ensuring direct thermal contact with the carbon fiber. The filter-scale uptake of 1.26 mmol g⁻¹ exceeds those of comparable fiber-based systems (0.65 mmol g⁻¹⁴; 0.39 mmol g⁻¹⁵), with stable cycling performance over 200 cycles (Supplementary Fig. 3).

After (Page 27-28):

A systematic comparison **with state-of-the-art regenerable CO₂ capture technologies, spanning leading amine-based sorbents and Joule-heating-based electrothermal systems, is provided in Supplementary Table 9 and Supplementary Note 8.** Lee et al.¹⁸ achieved 95% desorption in 10 min at 110 °C under 0.3 bar vacuum using PEI-impregnated mesoporous silica coated on carbon fibers for DAC. Lee et al.³³ developed silver nanocomposite-coated zeolite fibers with a partial vacuum-assisted e-TVSA cycle for DAC. Wu et al.³⁴ proposed a carbon nanofiber-based DAC air filter for building ventilation, though requiring off-site regeneration with filter replacement every two days. All three studies target DAC at 400 ppm, whereas the present work applies Joule-heating-based regeneration to indoor CO₂ at 1,000-2,000 ppm. The proposed filter achieves vacuum-free desorption (95% within 15 min at 100 °C), enabled by nonporous silica nanoparticles that minimize intra-particle diffusion resistance and a thin sorbent layer (14.7–46.1 μm) ensuring direct thermal contact with the carbon fiber. The filter-scale uptake of 1.26 mmol g⁻¹ exceeds those of comparable fiber-based systems (0.65 mmol g⁻¹¹⁸; 0.39 mmol g⁻¹³³), with stable cycling performance over 200 cycles (Supplementary Fig. 3). **While leading amine-based and structured sorbents attain higher intrinsic capacities (2–5**

mmol g⁻¹ at 400 ppm), they typically require vacuum- or steam-assisted regeneration and, in the highest-capacity cases, exhibit substantial capacity loss upon extended cycling; the present work instead prioritizes vacuum-free, low-temperature regeneration and system-level integration, and is the only entry in Supplementary Table 9 demonstrated at the system level.

Before:

Supplementary Table 8. Comparison of electrothermal CO₂ adsorbents with Joule-heating regeneration

Sorbent	Form factor	Heating element	Regeneration Method	Target Application	T _{ads} (K)	T _{des} (K)	t _{des} (min)	CO ₂ Uptake (mmol g ⁻¹)	Cyclic Stability	Ref
PEI/mesoporous silica	Powder coated fiber	Carbon fiber	ETSA + VSA	DAC (400 ppm)	30°C	90-110°C	19min (95%, 110°C, vacuum-assisted)	0.65 (Filter, 400ppm)	10 cycles	¹⁰
EDA-grafted Y zeolite	Powder coated fiber	Silver nanocomposite	ETSA + VSA	DAC (400 ppm)	25°C	110°C	90min (desorption cycle)	0.39-0.41 (Fiber, 400ppm)	4 cycles (dry, 5% loss) 10 cycles (humid, 12% loss)	¹¹
PEI/carbon nanofiber	Nonwoven filter	Carbon fiber	ETSA + Solar thermal	Distributed DAC (400 ppm)	25°C	80-105°C	1-2s Joule Heating + ~30min Solar Thermal	1.5 (Filter, 400ppm)	70 cycles (27.6% loss at 40cycles, then stable)	¹²
Amine-based ion exchange resin/Ag-coated glass flakes	3D-printed monolith	Ag-coated glass flakes	ETSA	DAC (400 ppm)	25°C	70°C	~1 min Joule Heating + ~60 min cycle	1.5 (Monolith, 9vol%, Dry) 0.5 (Monolith, 400ppm, Dry)	10 cycles	¹³
PEI/mesoporous carbon spheres	Spherical particles	Mesoporous carbon spheres	ETSA	Post-combustion (5-15%)	75°C	110°C	30min (ETSA)	3.7 (Powder, 15% CO₂, 75°C, Dry) 4.3 (Powder, 15% CO₂, 75°C, RH 60%)	10 cycles (3% loss)	¹⁴
SiC-PEI fiber CNT-zeolite fiber	Hollow fiber bundle	SiC or CNT	ETSA + VSA	Post-combustion (15%)	30°C	80-140°C	N/A	0.19 (SiC-PEI, 15% CO₂, Dry) 2.32 (CNT-zeolite, Fiber, 15% CO₂, Dry)	N/A	¹⁵
Zeolite Ti-Beta nanocrystals/carbon foam	Microcellular carbon foam	Carbon foam	ETSA	Post-combustion (0.15-1bar)	25°C	90-200°C	20min (87%, 150°C, vacuum-free)	4.6 (Powder, 1bar)	30 cycles (30% loss)	¹⁶
Zeolite NaUSY/activated carbon	Extruded monolith	Activated carbon	ETSA	Post-combustion (<10% CO ₂)	30°C	100-150°C	N/A	2.23 (Monolith, 20kPa)	N/A	¹⁷
PEI/nonporous silica	Powder coated fiber	Carbon fiber	ETSA	Indoor (1000-2000ppm)	25°C	60-100°C	15min (95%, 100°C, vacuum-free) 35min (95%, 80°C, vacuum-free)	1.84 (Powder, 1000ppm) 1.26 (Filter, 1000ppm)	200 cycles (2.4% mass loss, no capacity loss)	This Work

PEI : Polyethylenimine

EDA : Ethylenediamine

ETSA : Electrothermal Swing Adsorption

VSA : Vacuum Swing Adsorption

After (SI Page 34-35):

Supplementary Table 9. Comparison of electrothermal CO₂ adsorbents with Joule heating regeneration
Comparison of regenerable CO₂ capture technologies at the material, device, and system levels

Sorbent	Form factor	Heating element	Regeneration Method	Target Application	T _{ads} (K)	T _{des} (K)	t _{des} (min)	CO ₂ Uptake (mmol g ⁻¹)	Cyclic Stability	Demonstration Level	Ref
Benzylamine resin (Lewatit VP OC 1065)	Polymer beads	N/A	TVSA	DAC (400 ppm)	25°C	90–100 °C	N/A	0.95-1.1 (Beads, 400ppm, Dry)	N/A (oxidative degradation, >398 K)	Material	11-13
TEPA/SBA-15 (50 wt%, wet impregnation)	Powder	N/A	TSA	DAC (400 ppm)	25°C	110°C	15min	2.30 (Powder, 400 ppm)	10 cycles (dry, <5% loss)	Material	14
TEPA/CARIACT G-10 silica (50 wt%)	Powder	N/A	TSA	DAC (400 ppm)	25°C	100°C	15min	2.57 (Powder, 400ppm)	50 cycles (dry, 29% capacity loss, 55% amine loss)	Material	15
PEI/MCF on ceramic fiber honeycomb	Structured monolith (coated honeycomb)	N/A	S-TVSA	DAC (400 ppm)	25°C	105°C (steam)	~20min (>95%)	0.71 (Structured sorbent, 400ppm) 2.33 (powder, 400ppm)	100 cycles (no significant loss)	Device (filter)	16
Pyrazine-functionalized Co-MOF (1a')	Nanocrystals (hexahedral)	N/A	N/A	DAC (400 ppm)	25°C	N/A	N/A	1.36 (Powder, 400ppm) 5.7 (Powder, 10,000ppm)	N/A	Material	17
PEI/mesoporous silica	Powder coated fiber	Carbon fiber	ETSA + VSA	DAC (400 ppm)	30°C	90-110°C	19min (95%, 110°C, vacuum-assisted)	0.65 (Filter, 400ppm)	10 cycles	Device (filter)	18
EDA-grafted Y zeolite	Powder coated fiber	Silver nanocomposite	ETSA + VSA	DAC (400 ppm)	25°C	110°C	90min (desorption cycle)	0.39-0.41 (Fiber, 400ppm)	4 cycles (dry, 5% loss) 10 cycles (humid, 12% loss)	Device (fiber)	19
PEI/carbon nanofiber	Nonwoven filter	Carbon fiber	ETSA + Solar thermal	Distributed DAC (400 ppm)	25°C	80-105°C	1-2s Joule Heating + ~30min Solar Thermal	1.5 (Filter, 400ppm)	70 cycles (27.6% loss at 40cycles, then stable)	Device (filter, off-site regen.)	20
Amine-based ion exchange resin/Ag-coated glass flakes	3D-printed monolith	Ag-coated glass flakes	ETSA	DAC (400 ppm)	25°C	70°C	~1 min Joule Heating + ~60 min cycle	1.5 (Monolith, 9vol%, Dry) 0.5 (Monolith, 400ppm, Dry)	10 cycles	Device (monolith)	21
PEI/mesoporous carbon spheres	Spherical particles	Mesoporous carbon spheres	ETSA	Post-combustion (5-15%)	75°C	110°C	30min (ETSA)	3.7 (Powder, 15% CO ₂ , 75°C, Dry) 4.3 (Powder, 15% CO ₂ , 75°C, RH 60%)	10 cycles (3% loss)	Material	22
SiC-PEI fiber	Hollow fiber	SiC or CNT	ETSA + VSA	Post-combustion	30°C	80-140°C	N/A	0.19 (SiC-PEI,	N/A	Device (fiber)	23

CNT-zeolite fiber	bundle			(15%)				15% CO ₂ , Dry)		bundle)	
								2.32 (CNT-zeolite, Fiber, 15% CO ₂ , Dry)			
Zeolite Ti-Beta nanocrystals/carbon foam	Microcellular carbon foam	Carbon foam	ETSA	Post-combustion (0.15-1bar)	25°C	90-200°C	20min (87%, 150°C, vacuum-free)	4.6 (Powder, 1bar)	30 cycles (30% loss)	Device (foam)	²⁴
Zeolite NaUSY/activated carbon	Extruded monolith	Activated carbon	ETSA	Post-combustion (<10% CO ₂)	30°C	100-150°C	N/A	2.23 (Monolith, 20kPa)	N/A	Device (monolith)	²⁵
PEI/nonporous silica	Powder coated fiber	Carbon fiber	ETSA	Indoor (1000-2000ppm)	25°C	60-100°C	15min (95%, 100°C, vacuum-free) 35min (95%, 80°C, vacuum-free)	1.84 (Powder, 1000ppm) 1.26 (Filter, 1000ppm)	200 cycles (2.4% mass loss, no capacity loss)	System (DCV + ML control)	This Work

PEI : Polyethylenimine

EDA : Ethylenediamine

ETSA : Electrothermal Swing Adsorption

VSA : Vacuum Swing Adsorption

TVSA : Temperature Vacuum Swing Adsorption

S-TVSA : Steam-assisted Temperature Vacuum Swing Adsorption

MCF : Mesoporous cellular foam

DCV : Demand-Controlled Ventilation

ML : Machine Learning

Demonstration level is classified as follows. Material denotes CO₂ uptake measured at the powder- or bead-scale; Device denotes capture demonstrated in a structured or self-supporting form (e.g., coated fiber, monolith, or filter) that is not integrated into a ventilation system; and System denotes a capture device integrated and operated within a ventilation control framework. Studies employing off-site regeneration are classified as device-level, since capture and regeneration are not coordinated within a single operating system.

Reported CO₂ uptake values were obtained under heterogeneous conditions (CO₂ concentration, relative humidity, and sorbent form factor), and direct quantitative comparison should therefore be made with caution; where a study reports capacity on both a whole-composite and an adsorbent-only basis, both values are given.

Metal organic frameworks (MOFs) are included as high-surface-area benchmarks. Their exceptionally high BET areas afford very high CO₂ uptake at elevated concentrations, but their performance is strongly concentration-dependent and declines markedly at the low partial pressures relevant to indoor CO₂ management, as evident from the 400 ppm versus 10,000 ppm values.

Before:

Supplementary Note 8. Comparison with existing electrothermal CO₂ capture systems

To contextualize the performance of the proposed CO₂ capture filter, a systematic comparison with recently reported Joule-heating-based electrothermal adsorbents was conducted (Supplementary Table 7). Prior ETSA studies have predominantly targeted either direct air capture (DAC) at 400 ppm or post-combustion flue gas at 5-15 vol% (50,000-150,000 ppm).

To our knowledge, no previous study has applied Joule-heating-based regeneration to indoor CO₂ management at concentrations of 1,000-2,000 ppm.

After:

Supplementary Note 8. Comparison with existing electrothermal CO₂ capture systems

~~To contextualize the performance of the proposed CO₂ capture filter, a systematic comparison with recently reported Joule heating-based electrothermal adsorbents was conducted (Supplementary Table 7). Prior ETSA studies have predominantly targeted either direct air capture (DAC) at 400 ppm or post-combustion flue gas at 5-15 vol% (50,000-150,000 ppm). To our knowledge, no previous study has applied Joule-heating-based regeneration to indoor CO₂ management at concentrations of 1,000-2,000 ppm.~~

To contextualize the performance of the proposed CO₂ capture filter, a systematic comparison was conducted with state-of-the-art regenerable CO₂ capture technologies, encompassing both leading amine-based sorbents regenerated via conventional thermal swing processes (TSA/TVSA) and Joule-heating-based electrothermal systems, classified according to their demonstration level: material, device, and system (Supplementary Table 9). Prior studies have predominantly targeted either direct air capture (DAC) at 400 ppm or post-combustion flue gas at 5–15 vol% (50,000–150,000 ppm); no previous study among those surveyed has applied Joule-heating-based regeneration to indoor CO₂ management at concentrations of 1,000–2,000 ppm.

Material-level benchmarks:

Among leading amine-based sorbents evaluated under low-concentration (400 ppm) conditions, TEPA- and PEI-impregnated mesoporous silica achieve 2.30–2.57 mmol g⁻¹, substantially exceeding the present sorbent (1.84 mmol g⁻¹ at the powder scale under 1,000 ppm). Lewatit VP OC 1065, a widely used amine-functionalized resin regarded as a commercial DAC benchmark, exhibits approximately 0.95–1.1 mmol g⁻¹ at 400 ppm under dry conditions¹¹⁻¹³, comparable to the present material. Metal organic frameworks (MOFs) are included as high-surface-area benchmarks: their exceptionally high BET areas afford very high CO₂ uptake at elevated concentrations, but their performance is strongly concentration-dependent and declines markedly at the low partial pressures relevant to indoor air. This is evident from the pyrazine-functionalized Co-MOF, which adsorbs 5.7 mmol g⁻¹ at 10,000 ppm but only 1.36 mmol g⁻¹ at 400 ppm¹⁷, underscoring that intrinsic capacity measured at elevated concentration is not a reliable indicator of trace-CO₂ performance. Importantly, however, these higher-capacity sorbents entail operational trade-offs: TEPA-impregnated silica, for instance, suffers up to ~29% capacity loss over 50 cycles with ~55% amine loss through volatilization, whereas the present filter retains full capacity over 200 cycles.

Device-level benchmarks:

Lee et al.¹⁸ demonstrated sorbent-coated carbon fibers for DAC using PEI-impregnated mesoporous silica, achieving 95% desorption in 10 min at 110 °C under 0.3 bar vacuum. Lee

et al.¹⁹ further advanced the electrified fiber concept using silver nanocomposite-coated EDA-grafted Y zeolite fibers, reaching a desorption temperature of 110 °C within 80 s through a partial vacuum-assisted four-step ETSA cycle (90-min total desorption). Wu et al.²⁰ proposed a carbon nanofiber (CNF)-based PEI DAC air filter for building ventilation, with high uptake (4.0 mmol g⁻¹ under 68% RH at 400 ppm) regenerable via Joule heating and solar thermal energy; however, their system requires off-site regeneration with filter replacement every two days and transport to centralized processing facilities. Among structured DAC sorbents, Wu et al.¹⁶ reported 0.71 mmol g⁻¹ (composite basis; 2.33 mmol g⁻¹ on an adsorbent basis) at 400 ppm using PEI-impregnated mesoporous cellular foam coated on a ceramic honeycomb with 100-cycle stability, though regeneration relies on steam-assisted temperature vacuum swing adsorption (S-TVSA) with a high-temperature steam supply, which is impractical for occupied indoor spaces.

In contrast, the present system achieves rapid desorption under atmospheric pressure, 95% regeneration within 15 min at 100 °C and within 35 min at 80 °C, without vacuum assistance. The favorable desorption kinetics observed in the present system can be attributed to the sorbent and the spray coating process. Lee et al.¹⁸ employed mesoporous silica (SYLOID C-803) in which PEI is confined within mesopore channels, creating substantial intra-particle diffusion resistance during CO₂ release. In the present work, nonporous silica nanoparticles (60-70 nm) were used, positioning the amine functional groups predominantly on the external particle surface and thereby minimizing the CO₂ diffusion pathway during thermal desorption. Additionally, the thin sorbent layer (14.7-46.1 μm) produced by spray coating provides direct thermal contact with the Joule-heated carbon fiber, enabling rapid and uniform heat delivery to the adsorbent. The elimination of vacuum pumps significantly simplifies the system design and removes the associated noise and energy penalty, which is an essential consideration for deployment in occupied indoor spaces.

The filter-scale CO₂ uptake of 1.26 mmol g⁻¹ (1.84 mmol g⁻¹ at the powder scale) under 1,000 ppm at 25 °C is comparable to or exceeds those of other fiber-based ETSA systems on a coated-fiber mass basis, such as 0.65 mmol g⁻¹ (Lee et al.¹⁸) and 0.39 mmol g⁻¹ (Lee et al.¹⁹, Ag-coated fiber basis). The system also demonstrated superior cyclic stability, retaining full CO₂ capture capacity with a 2.28% increase over 200 adsorption–desorption cycles, compared to the 27.6% capacity loss within 40 cycles reported for the CNF-based adsorbent by Wu et al.²⁰. Finally, unlike all cited studies that remain at the material-level demonstration, this work extends to system-level validation by integrating the CO₂ capture filter with a demand-controlled ventilation (DCV) framework and deep learning-based real-time control, achieving up to 28.3% ventilation energy savings compared to conventional DCV systems.

HVAC-integrated systems:

Beyond material-level benchmarks, the integration of CO₂ capture units into HVAC systems has also been explored, primarily through simulation studies. Abdullatif et al.²⁶ thermodynamically evaluated a temperature–vacuum swing adsorption (TVSA) direct air capture unit placed at six locations within an air handling unit under Qatar summer conditions, showing that integration improves capture efficiency (e.g., from 5.3% to 27.19% for the exhaust-stream position) and that full air recirculation with the capture unit reduces the HVAC cooling load by 44%. Xu et al.²⁷ developed a Modelica-based model of a TVSA capture unit embedded in the return-air loop of a typical HVAC system and reported a 16.13% reduction in energy consumption together with a 23.62% decrease in average indoor CO₂ concentration when combined with CO₂-based demand-controlled ventilation in a winter month. These studies clearly demonstrate the energy-saving potential of capture–ventilation integration;

however, both rely on numerical models parameterized with literature isotherm data for a commercial sorbent (Lewatit VP OC 1065), employ vacuum-assisted TVSA regeneration ($P_{\text{des}} = 20 \text{ kPa}$, $T_{\text{des}} = 373 \text{ K}$), and adopt fixed or threshold-based control logic. In contrast, the present CDCV framework is built upon an experimentally fabricated and cyclically validated filter that is regenerated by vacuum-free Joule heating at $80\text{--}100 \text{ }^\circ\text{C}$, and its capture, regeneration, and ventilation operations are adaptively coordinated by a deep-learning-based controller, thereby extending prior simulation-oriented integration studies toward an experimentally grounded, control-integrated implementation.

System-level demonstration:

Finally, unlike all cited studies, which remain at the material or device level, this work extends to system-level validation by integrating the CO_2 capture filter with a DCV framework and deep-learning-based real-time control, achieving up to 28.3% ventilation energy savings compared with conventional DCV systems.

Alternative strategies considered:

It is also worth noting that alternative CO_2 capture strategies were considered but deemed unsuitable for the intended indoor application. Liquid amine scrubbing (e.g., aqueous MEA solutions) requires regeneration temperatures of $120\text{--}140 \text{ }^\circ\text{C}$ ²⁸ with reboiler duties of $3.8\text{--}4.2 \text{ GJ t}^{-1}\text{CO}_2$ ²⁹, and is known to emit volatile degradation products including ammonia, aldehydes, and potentially carcinogenic nitrosamines during thermal cycling³⁰, posing unacceptable health risks in enclosed indoor spaces where stack-based atmospheric dispersion is unavailable. Metal-organic frameworks, while offering high surface areas and tunable pore structures, suffer from significant capacity reduction under humid conditions³¹ and involve more complex and costly synthesis processes compared to commercially available amine-functionalized silica³². Zeolite-based physisorbents typically require regeneration temperatures of $150\text{--}250 \text{ }^\circ\text{C}$ ³³ and exhibit up to 93% capacity loss at 74% relative humidity³⁴, making them incompatible with the moderate-temperature, humidity-tolerant operation required for indoor environments.

Reviewer #3 (Remarks to the Author):

The paper is now ready for publication.